The 52-Week High and Momentum Investing:

Implications for Asset Pricing Models

João Miguel Morim Meira Fernandes

199303842@fep.up.pt

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Supervisor:

Júlio Fernando Seara Sequeira da Mota Lobão, PhD

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Biographical Note

João Miguel Morim Meira Fernandes was born on the 23rd of October 1975, in Póvoa de Varzim. He currently resides with his wife and two young sons in Porto.

In 1993 he was admitted to the 5-year Economics degree in Faculdade de Economia do Porto, which he completed successfully in 1998. In 2013 he enrolled in the Master in Finance, also at Faculdade de Economia do Porto, in order both to improve and refresh his knowledge and qualifications in all finance subjects.

Professionally, his career has been inextricably linked to the Portuguese banking sector, having successively worked in the Corporate Credit Departments of Banco Mello, Millennium bcp and Banif. Since 2014 he leads the Rating Department at Banif managing a team of 6 dedicated and experienced Financial Analysts.

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Abstract

The momentum effect identified by Jegadeesh and Titman (1993) is considered by Fama and French (1996) as the main embarrassment to their 3-factor asset pricing model. Carhart (1997) proposes a 4-factor model by adding a momentum factor. However, George and Hwang (2004) find that a strategy based on the nearness of a stock's price to its 52-week high dominates all other momentum effects. Following George and Hwang (2004), we propose a variation of the Carhart (1997) 4-factor model, with the momentum risk factor constructed according to the 52-week high strategy. To the best of our knowledge, there is no previous formalization of this specific model in the literature. Our findings confirm the existence of an abnormal, but statistically insignificant return, of the 52-week high strategy in the US market from 1980 to 2014. The performance is very different, however, for subsample periods, with significant positive returns in 1980-2000, in line with George and Hwang (2004), and insignificant negative returns in the later subperiod sample of 2001-2014. We proceed to test and compare all three models on the 25 size-BE/ME and 25 size-momentum Fama-French portfolios, according to the approach of Fama and French (2012). The inclusion of a momentum factor does not significantly add to the 3-factor model on the 25 size-BE/ME portfolios. On the tests on the 25 size-momentum portfolios, our model seems to clearly reduce the regressions' intercepts relative to the 3-factor model, but falls short from the Carhart (1997) model. We also address the 25 size-momentum portfolios subsamples from 1980-2000, finding results in line with the complete sample, and from 2001-2014 when the contribution of both the Carhart (1997) and our 4-factor models' is negligible relative to the 3-factor model. Notwithstanding, the period 2001-2014 seems in part to be influenced, and in accordance with Daniel and Moskowitz (2014), by the momentum crash of 2009. In sum, our results indicate that, in order to capture the anomaly, the 3-factor model requires the introduction of a momentum factor, but that the Carhart (1997) 4-factor model consistently surpasses our model.

Key Words: 52-week high, momentum, asset pricing models.

JEL-Codes: G12, G14, G15.

Resumo

O efeito de *momentum* de Jegadeesh e Titman (1993) é considerado por Fama e French (1996) como o principal constrangimento para o seu modelo de 3-factores. Carhart (1997) propõe adicionar um quarto factor de forma a capturar este efeito. Contudo, George e Hwang (2004) demonstram que uma estratégia baseada na proximidade do preço de uma acção ao seu máximo das últimas 52 semanas domina as restantes estratégias de *momentum*. Seguindo George e Hwang (2004), propomos uma variação do modelo de Carhart (1997), com o factor de *momentum* construído de acordo com a estratégia proposta pelos autores. Tanto quanto seja do nosso conhecimento, não existe prévia formalização deste modelo na literatura. Os nossos resultados confirmam a existência de um anormal, mas estatisticamente insignificante retorno, da estratégia de George e Hwang (2004) no mercado dos EUA entre 1980 e 2014. Contudo, os resultados são muito diferentes para as subamostras, com retornos significativamente positivos em 1980-2000, em linha com George e Hwang (2004), e insignificantemente negativos no posterior subperíodo amostral de 2001-2014. Procedemos à comparação os 3 modelos nos 25 portfólios dimensão-BE/ME e 25 portfólios dimensão-*momentum* de Fama-French, de acordo com a metodologia de Fama e French (2012). A introdução de um factor de *momentum* não é relevante nos 25 portfólios dimensão-BE/ME. Nos testes dos 25 portfólios dimensão-*momentum*, o nosso modelo parece reduzir os alfas, mas ficando aquém do modelo de Carhart (1997). Relativamente aos 25 portfólios dimensão-*momentum* abordámos ainda as subamostras de 1980-2000, com resultados em linha com o obtido para a amostra completa, e de 2001-2014 em que o contributo tanto do nosso modelo como o de Carhart (1997) é negligenciável face ao modelo de 3-factores. Todavia, o período 2001-2014 parece estar, em parte, e em acordo com Daniel e Moskowitz (2014), influenciado pelos resultados muito negativos das estratégias de *momentum* em 2009. Em suma, os resultados parecem recomendar a introdução de um factor de *momentum*, mas com consistente vantagem para o modelo de Carhart (1997).

Palavras-Chave: máximo de 52 semanas, *momentum*, modelos de avaliação de activos.

Códigos JEL: G12, G14, G15.

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1. Introduction

The Efficient Market Hypothesis (EMH), as formulated by Fama (1965, 1970), has played a crucial role in finance theory, supplying the basis for the development of most asset-pricing models while remaining one of its most disputed foundations.

In fact, several deviations to the EMH have been documented in the literature, providing compelling evidence that markets do not follow a random walk. Among these anomalies, the momentum effect of Jegadeesh and Titman (1993) remains one of the most relevant, as the strategy provides significant abnormal returns, is computed using readily and publicly available information, and persists in subsequent studies. The implications are especially relevant as concerns asset pricing models, since the effect is not captured by the CAPM or by the 3-factor model of Fama and French (1993, 1996), the latter considering momentum as the main embarrassment to their model. Addressing this limitation, Carhart (1997) proposes an expansion of the 3-factor model by including a fourth factor, aimed at capturing the Jegadeesh and Titman (1993) momentum effect.

However, George and Hwang (2004) provide an important extension to the momentum literature, by suggesting a strategy based on the nearness of a stock's price to its 52-week high, not only achieving returns in line with previous strategies, but also dominating other momentum strategies while not experiencing long-term reversals. Several studies applying George and Hwang (2004)'s methodology to different markets and geographies, such as Du (2008), Liu *et al.* (2011) and Li and Yu (2012), generally confirm the abnormal returns of the 52-week high strategy. These results also put into question current theory about momentum that tries to reconcile momentum and long-term mean reversion, such as overreaction or slow diffusion of information, suggesting instead that the answer may reside in an anchor-and-adjust bias by the investors.

Based on these empirical findings, our intuition is relatively straightforward: if the 52-week high dominates the relative strength momentum strategy, and additionally there is no evidence of long-term mean reversion, the former must also be a superior basis on which to build a momentum risk factor. Our aim in the present dissertation is, then, to develop and test a new 4-factor model, succinctly a variation of Carhart (1997)'s 4-factor model, by building the momentum risk factor according to George and Hwang (2004) instead of Jegadeesh and Titman (1993). As to provide a benchmark against which to compare the results of our own model we also test the 3-factor and Carhart (1997) 4-factor models for the same data. The tests follow the approach of Fama and French (2012), basically by doing time-series regressions on a series of 25 size-BE/ME and 25 size-momentum portfolios, focusing on the US market, from 1980 to 2014, with data collected from DataStream and from Kenneth R. French's website[1].

We must stress that, to the best of our knowledge, there is no previous suggestion of such a model in the literature. Even though the model lacks a strong theoretical basis, if the intuition proved to be correct, and the results surpassed those of previous models', it would not only add significantly to the on-going debate about market efficiency, but also contribute to the explanation of the momentum effect, increasing the evidence of psychological factors playing a relevant role in the formation of stock prices. The implications would then be significant not only for theoretical purposes, since it would point to the need of improving on the anchor-and-adjust bias as an explanation for momentum, but also for practical applications since such a model could eventually improve estimates of financial asset prices or the cost of capital.

Succinctly, we find that George and Hwang (2004) momentum is small and statistically insignificant for the US stock market, from 1980 to 2014, though subperiod analysis shows results in line with the literature from 1980 to 2000 and its apparent disappearance, with negative average returns, in the later period of 2001 to 2014. Results are qualitatively similar though, contrarily to George and Hwang (2004), much stronger for Jegadeesh and Titman (1993) momentum. We also find, in accordance with Daniel and Moskowitz (2014), that, due to their reliance on the continuation of returns, following persistently bear markets and contemporaneously with fast market reversals, momentum experiences crashes. We show that such a particular, and especially strong, crash occurred in 2009, which may drive the results for subperiod 2001-2014.

The tests on the asset pricing models show that, at worse, the inclusion of a momentum risk factor does not have an influence on their ability to capture the 25 size-BE/ME Fama-French portfolios' excess returns. However, for the 25 size-momentum portfolios, the inclusion of a momentum risk factor is generally crucial, with the performance of the Carhart (1997) 4-factor model consistently surpassing that of our proposed 52W 4-factor model. The only exception is for the subperiod 2001-2014, in

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

which, as addressed, the momentum effect seems to disappear and the performance of both 4-factor models is very similar to that of the 3-factor model. Again that seems, at least in part, to rise from the influence of the momentum crash of 2009. If we exclude that year, momentum stages a reappearance, though somewhat more subdued, and the necessity of a momentum factor is, as for the complete sample, once again made clear.

Considering our results, and though as a whole they are not incompatible with the anchor-and-adjust bias, the performance of the George and Hwang (2004) momentum strategy on the subperiod 2001-2014 does not allow us to exclude the possibility that this effect has been absorbed by the market. However, Jegadeesh and Titman (1993) momentum seems to continue to show some resilience. It is possible, as such that the explanation for momentum may lie in the traditional underreaction-overreaction area.

Over the next chapters, we provide a review of the main literature concerning momentum and the 52-week high in section 2, address our view of the implications of George and Hwang (2004) for asset pricing models in section 3, describe the methodology in section 4, present our findings in section 5, and conclude in section 6.

2. The 52-Week High and Momentum: A Literature Review

In the present section we start by presenting a brief overview of the momentum literature in subsection 2.1, address the main theories of momentum in subsection 2.2, and, finally, concentrate on George and Hwang (2004)'s 52-week high momentum strategy, also considering the main related studies, in subsection 2.3.

2.1. The Efficient Market Hypothesis and the Momentum Effect

Ever since it was formally proposed by Fama (1965, 1970), the Efficient Market Hypothesis (EMH) has come to dominate financial literature, providing the theoretical basis for a large branch of academic research and the framework on which stand the most widely applied asset-pricing models.

The EMH can be summarized as the simple statement that prices of financial assets reflect all available information and that, as a result, prices can be considered as a fair representation of the financial assets' intrinsic value.

There is, however, substantial evidence that financial assets' prices do not follow a random walk and that returns are predictable, by variables both at the aggregate and firm level, such as identified by Fama and French (1989) for business conditions, Basu (1977), Bhandari (1988) and Fama and French (1992) for indicators at the firm level or Lee and Swaminathan (2000) for trading volume. The empirical studies asserting that there is some degree of predictability to returns are generally referred to as the anomalies literature. Among these anomalies, the momentum effect represents one of the most serious challenges to the EMH hypothesis under its weak form, as it implicates that it is possible to achieve abnormal returns using widely available public information.

Jegadeesh and Titman (1993) conclusively identified the momentum effect in their defining paper, documenting that a strategy that buys stocks that have performed well and sells stocks that have performed poorly in the past generates relevant positive returns over different 3- to 12- months selecting and holding periods. The authors' analysis of NYSE and AMEX stocks achieves significant abnormal returns in the 1965 to1989 sample period, for all different selecting and holding periods, with the 6-

month/6-month strategy compounding an excess return of 12.01% per year. A decomposition of these profits indicates that they are not due to the systematic risk of the strategies, nor to delayed reaction to information about a common factor, though it is consistent with delayed reactions to firm-specific information. However, further tests suggest the abnormal returns yielded by the strategy may not be permanent, as stocks included in the relative strength portfolios exhibit reversion for longer holding periods, experiencing negative abnormal returns starting around 12 months after the formation date and continuing up to the thirty-first month.

Moskowitz and Grinblatt (1999) use CRSP and COMPUSTAT data files to construct 20 value-weighted industry portfolios for every month from July 1963 to July 1995, implementing a momentum strategy that consists in buying stocks from winning industries and selling stocks from past losing industries. The paper focuses on horizons of 6- to 12- months finding, in particular, strong evidence that persistence in industry return components may account for much of the profitability of individual stock momentum strategies, which are less profitable and significantly weaker once controlled for industry effects. Industry portfolios exhibit significant momentum, even after controlling for size, book-to-market equity (BE/ME), individual stock momentum, the cross-sectional dispersion in mean returns, and potential microstructure influences. Unlike the individual stock momentum, industry momentum is strongest in the 1-month horizon but the abnormal returns tend to similarly dissipate after 12 months, eventually also showing signs of reversal in longer horizons.

Similar results are found by Rouwenhorst (1998), who applies Jegadeesh and Titman (1993)'s strategy to 12 European countries[1], from 1978 to 1995, concluding that an internationally diversified relative strength portfolio that invests in medium-term winners and sells medium-term losers earns approximately 1 percent per month. The effect is present in all 12 countries in the sample, lasts for about 1 year, holds across all decile sizes despite being stronger for small firms, and is not attributable to conventional measures of risk. It is, however, correlated to the momentum effect observed in the US market suggesting it may be driven by a common factor. Additionally, Rouwenhorst (1999) concurrently finds that results for 20 emerging

[1] Austria, Belgium, Denmark, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, and UK.

markets[2] are qualitatively similar to those of the developed markets.

It is worthwhile to mention that a seminal paper by De Bondt and Thaler (1985) focusing on NYSE common stocks, between January 1926 and December 1982, as compiled by the CRSP, identifies the opposing effect of mean-reversion in the long-term. Specifically, they find that past loser portfolios outperform the market by, on average, 19.6%, while past winner portfolios earn about less 5% than the market, over the 36 months following the portfolios' formation. There are some additional noteworthy particularities to the results, namely the fact that the effect is asymmetrical, being much greater for losers than for winners, and secondly that most of the excess returns are realized in January. The empirical evidence seems, then, as concerns investor over- and underreaction, to point to seemly distinct types of anomalies in the stock market, momentum and mean-reversion, for different time horizons.

Lee and Swaminathan (2000), in their study on the implications of trading volume in NYSE and AMEX stocks between January 1965 to December 19995, which they deem to show is related to misperceptions about a firm's future earning prospects, find that it is possible to create Jegadeesh and Titman (1993) style momentum portfolios that exhibit return reversals of the type documented by De Bondt and Thaler (1985). An implication is that trading volume might provide a link between those two effects, proposing that stocks may follow a life cycle of relative glamour and neglect, with trading volume proving useful for identifying where a stock is in this cycle.

Jegadeesh and Titman (2001) again return to the problem of momentum in the NYSE, AMEX and Nasdaq stock markets, with additional 9 years of data, finding that the strategy maintains its profitability. This is especially noteworthy considering that, as reported by Schwert (2003), other anomalies have tended to disappear following the original studies. However, evidence about reversals for longer holding periods depends on the composition of the sample, the sample period and risk-adjustment.

Presently, the momentum effect continues to be a controversial and much debated topic in the literature, as exemplified by more recent papers, such as Chui *et al.* (2010) and Israel and Moskowitz (2013). Chui *et al.* (2010) address the cross-country cultural differences influence on momentum profits, finding that individualism is positively associated with momentum, as well as with trading volume and volatility. Though other

[2] Argentina, Brazil, Chile, Colombia, Greece, India, Indonesia, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, Taiwan, Thailand, Turkey, Venezuela, and Zimbabwe.

aspects also influence momentum, both positively such as information dispersion, transaction costs or familiarity of the market to foreigners, or negatively such as firm size and volatility, the addition of these variables does not stifle the relation between momentum and individualism. Israel and Moskowitz (2013) address the role of shorting, firm size and time, on size, value and momentum strategies, both in the US stock market, between July 1926 and December 2011, and in the international stock markets and other nonstock asset classes, from February 1972 to December 2011. The authors find that long positions explain almost all of size, 60% of value and 50% of momentum profits. Shorting becomes less important for momentum and more important for value strategies as firm size decreases. The value premium is inversely related to firm size, but contrary to the previous literature, there appears to be no relation between size and momentum. There also seems to be no significant effect of changes in trading costs or institutional or hedge fund ownership on the profits of the strategies.

2.2. Current Theory of Momentum

The earliest theories proposed in the literature, as regards the momentum effect, tend to focus either on the hypothesis of underreaction or overreaction by the traders, and the effects of those attitudes on the movement of prices.

De Bondt and Thaler (1985) propose that the observed mean reversion in longer horizons is consistent with the hypothesis of overreaction by traders to new information that, when corrected, generates reversion of stock prices in the long run. However, they are not able to explain several aspects of the results, most importantly the large positive excess returns earned by the loser portfolio every January.

Jegadeesh and Titman (1993) contend that the initially positive and later negative relative strength returns suggest that the interpretation of return reversals as evidence of overreaction, and return persistence as evidence of underreaction, is probably simplistic. A possible interpretation is that transactions by investors who buy past winners and sell past losers move prices away from their long-run values temporarily and thereby cause prices to overreact, consistently with the analysis of De Long *et al.* (1990) of "positive feedback traders". Another alternative would be that the market underreacts to information about the short-term prospects of firms but overreacts to information about their long-term prospects, given the different nature of the information available for each time frame.

More recently, Daniel *et al.* (1998), Barberis *et al.* (1998) and Hong and Stein (1999), have contributed decisively to a new branch of research, referred to as behavioral finance, providing some interesting insights while also seeking to reconcile the momentum and mean-reversion effects.

Daniel *et al.* (1998)'s model is based on investor overconfidence and asymmetric shifts in confidence arising from biased self-attribution. In particular, the theory pertains that investors overestimate their own ability to generate information, or to identify the significance of existing data that others neglect, thereby underestimating the public signals and their own forecast errors. Conversely, it proposes that there is a bias in self-attribution, meaning that as individuals observe the outcomes of their actions, they update their confidence in their own ability in a biased manner. To put it in another way, the confidence of the investors grows when later public information confirms the validity of their actions, but it does not fall proportionately if it contradicts their private information. The combination of these effects would reconcile the momentum and mean reversion effects, since as investors assign excessive weight to successful trades as a result of own ability, while underweighting disconfirming information, this would justify the momentum effect observed in the short run, which eventually reverses as further public information draws the price back to fundamentals.

Barberis *et al.* (1998) propose a model of investor sentiment based on the representativeness heuristic and conservative bias. The representative heuristic implies that there is a tendency for investors to view stocks as representative of a certain class, independent of the laws of probability, meaning that investors may project that firms with extraordinarily high (low) past results will continue to obtain extraordinarily high (low) future results. Simultaneously, the authors contend that investors exhibit a conservative bias defined as the slow updating of models in the face of new evidence. The implication is that momentum would be consistent with overreaction arising for stocks with a series of good or bad news, as investors project the continuation of returns, and are slow, when new information arrives, to update their prior assumptions. Although the conservatism bias, by itself, leads to underreaction, in conjunction with the representative heuristic it may also explain mean reversion in longer horizons.

In Hong and Stein (1999)'s model the emphasis is on the interaction between heterogeneous agents rather than in assigning particular biases to a representative agent. The model divides investors into two categories, "newswatchers" and "momentum traders", both boundedly rational in the sense that each is only able to process some subset of publicly available information. The newswatchers make forecasts based on their private observations about future fundamentals, disregarding current or past prices, while momentum traders condition their forecasts on past price changes with the limitation that these forecasts are simple functions of historical prices. In addition to those constraints on the abilities of investors, it is assumed that private information diffuses gradually among the newswatchers. The interaction proceeds as follows: the slow diffusion of information among newswatchers causes underreaction in the adjustment of prices to new information; it would be expected that momentum traders contribute to the correction of prices towards fundamentals but, as they are limited to simple strategies, the perverse effect is that these strategies lead to overshooting the fundamental value. The model unifies underreaction and overreaction in the sense that they both ascend from the interaction between the two different types of traders.

In Lee and Swaminathan (2000), consistently with the behaviorists, the market is presented as in a constant state of convergence toward fundamental value, with intermediate-term "underreaction" and long-term "overreaction" simply being two elements of the same continuous process by which prices reflect new information. According to the authors' Momentum Life Cycle hypothesis, stocks experience periods of investor favoritism and neglect with trading volume providing useful information in locating a given stock in its life cycle. High volume winners and low volume losers would be regarded as late stage momentum stocks, as the momentum is more likely to reverse in the near future, while low volume winners and high volume losers would be considered early stage momentum stocks, as the effect is more likely to persist.

Other models, such as Klein (2001) and Grinblatt and Han (2005), expand on the finding by Tversky and Kahneman (1974) of the psychological effect referred to as adjustment and anchoring bias.

Klein (2001) suggests that long-term reversals arise as a result of investors accrued capital gains, in particular of the impact of taxes on the utility-maximizing behavior of rational investors, with the acquisition price acting as the anchor. In this model the demand for stocks of a firm is positively related to the imbedded capital gain, as investors with too many stocks of a company that has done well will sell fewer shares than they would in the absence of the capital gains tax. On the other hand, investors with too few stocks do not feel a similar pressure, leading to a higher equilibrium price. The higher equilibrium price also implies that expected returns for subsequent periods are lower, consistent with the observed mean-reversion in longer horizons.

Grinblatt and Han (2005) use the prospect theory and mental accounting frameworks to explain momentum in the cross-section of stock returns. In short, the authors propose that one class of investors are subject to a disposition effect, which makes them averse to selling stocks when that results in the recognition of losses, and more likely to sell the stocks when there are unrealized gains. The anchor is also the acquisition price but, in this case, the demand functions are negatively related to embedded capital gains, as these investors have demand distortions that are inversely related to the unrealized returns on a stock. Consequently, stocks that have had positive news experience excess selling pressure relative to those affected by negative news, generating underreaction to public information, leading to undervaluation of past winners and overvaluation of past losers. Once prices revert to their fundamental value, which in the model eventually occurs as a result of the assumption that investors have heterogeneous utility curves, this leads to the observed momentum effect. It is interesting to point out that Grinblatt and Han (2005) find that, once controlled for capital gains relative to the acquisition price anchor, the Jegadeesh and Titman (1993) momentum effect largely disappears.

Finally, as summarized by Vayanos and Woolley (2013), the rational models of momentum include Berk *et al.* (1999), Johnson (2002) and Shin (2006), which assume symmetric information, and Albuquerque and Miao (2014) and Cespa and Vives (2014), that assume asymmetric information. In any case, the expected return of a risky asset decreases following a low past return, generally as a result of the concurrent decrease in volatility or of the assets' supply, resulting in the momentum effect.

2.3. The 52-Week High and Momentum Investing

In the current subsection we present a detailed description of George and Hwang (2004), as well as a brief overview of the main subsequent papers concerning the 52-week high strategy, given our hypothesis concerning the implications of these findings for asset pricing models, as more thoroughly discussed in section 3.

2.3.1. George and Hwang (2004)

The seminal paper by George and Hwang (2004) examines how a readily available piece of information, specifically the nearness of a stock's price to its 52-week high, is able to explain most of the profits from momentum investing.

The focus on the 52-week high is justified by the fact that previous models predicted that investors were either slow to react, or overreacted, to new information. A stock at or near its 52-week high is one for which good news has recently arrived, and may be a time when biases in how traders react to news are at their peaks, making this the ideal time to address the impact of momentum.

The dataset is composed of all the stocks on CRSP from 1963 to 2001, and the main focus is on the 6-month/6-month strategy, analyzing and comparing the momentum strategy based on the nearness to the 52-week high proposed by George and Hwang (2004) with the strategies proposed by Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999). The authors find that the returns of the strategies are all very close for the sample period, though much higher for the 52-week high and Jegadeesh and Titman (1993) strategies if January is excluded. However they capture different effects as is highlighted by the pairwise comparisons between 52-week high and Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999) strategies.

Another approach is to combine all three strategies on Fama and MacBeth (1973) style cross-sectional regressions, both as raw and as risk-adjusted returns (according to Fama and French (1993, 1996)'s model). This method again indicates that nearness to the 52-week high is a better predictor of future returns than either Jegadeesh and Titman (1993) or Moskowitz and Grinblatt (1999), suggesting that price level relative to an anchor may be more descriptive than previous theories.

An additional finding is that, contrary to Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999), there is no clear evidence of reversal for either winners or losers in the 52-week high strategy, indicating that momentum and mean reversion may be separate effects. The implication is that, if the predictive ability of the 52-week high is related to an anchor-and-adjust bias, when traders correct their initial bias they do not over- or undercorrect, but adequately adjust to the fundamental value.

Although the findings are consistent with Grinblatt and Han (2005), the interpretation is distinct, as in that model the anchor is the acquisition price. Adding Grinblatt and Han (2005)'s measure of embedded capital gains to the cross-sectional regressions, and though the results are in line with that theory's proposition, the 52-week high strategy still dominates all other strategies.

The results are robust for other time frames discussed in the literature, being even stronger for longer time frames, while continuing to exhibit no signs of reversal.

In conclusion, the evidence seems to point to an anchoring effect of the 52-week high, meaning that when the price is near the 52-week high traders are reluctant to bid up even if new information warrants it; similarly, they are unwilling to sell as low as implied by new negative information when the price is farther from the 52-week high. When the information eventually prevails, momentum occurs, but since traders adequately correct their priors this justifies the absence of mean reversion.

2.3.2. Evidence from Other Markets and Geographies

In the 10 years since the publication of George and Hwang (2004)'s paper, notwithstanding the important implications of their findings, the studies applying the methodology to other markets are still in relatively small number, although covering already a lot of ground concerning both geographical and distinct financial markets.

Marshall and Cahan (2005) use Australian stock data, between 1991 and 2003, to provide the first out-of-sample test of the 52-week high, finding that the strategy is very profitable for stocks in which short-selling has been approved. The profitability is robust to different size and liquidity, also outperforms both Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999), and persists after risk-adjustment.

Du (2008) applies the 52-week high strategy to MSCI country indices for 18 developed markets[3], between 1969 and 2004, finding, consistently with George and Hwang (2004), that the strategy dominates past returns in terms of predictability and largely explains momentum profits. However, differently from the original paper, short-term momentum coexists with long-run reversals, even after risk-adjustment, suggesting investors may still overreact when correcting the initial bias.

Gupta *et al.* (2010) compare Jegadeesh and Titman (1993), Moskowitz and Grinblatt (1999) and 52-week high strategies, for a sample of 51,879 stocks originating from 51 countries[4], between 1973 and 2007, finding that all strategies are profitable, and that the anomaly appears in all major markets, but that Jegadeesh and Titman (1993) dominates both Moskowitz and Grinblatt (1999) and the 52-week high.

The Latin American markets of Argentina, Brazil, Chile and Mexico are studied by Abinzano *et al.* (2010), finding that momentum is present in all except Argentina, with the evidence for Mexico consistent with a reference price strategy while in Brazil and Chile it conforms with overreaction and long-term reversion. However, the interaction between overreaction and the disposition effect, dependent on factors such as market state, is crucial in explaining the momentum effect.

Sapp (2010) studies the performance of the same three strategies for mutual funds, examining equity funds in the CRSP Mutual Fund database, from 1970 to 2004, using an analogous 1-year high measure for the net asset value (NAV) of mutual fund shares. The author finds that all have significant, independent and predictive ability for fund returns, and that each measure produces distinctive patterns in momentum profits.

Burghof and Prothmann (2011) address whether the 52-week high strategy is, as would be expected, stronger when there is greater information uncertainty, for which six proxies are used: firm size, book-to-market ratio, distance between the 52-week high and the 52-week low, stock price volatility, firm age and cash-flow volatility. Using data from the UK stock market, dating from 1989 to 2008, the authors find that, for all six proxies, greater information uncertainty leads in fact to higher profitability of the

[3] Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, UK and US.

[4] Argentina, Australia, Austria, Bangladesh, Belgium, Brazil, Canada, Chile, China, Colombia, Cyprus, Czech Republic, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Kenya, Lithuania, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Pakistan, Philippines, Poland, Portugal, Romania, Singapore, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Thailand, Turkey, UK, and US.

strategy, robust even after controlling for risk, industry and turn-of-the-year effect, providing evidence that anchoring explains the 52-week high returns.

Liu *et al.* (2011) study the 52-week high strategy in 20 international stock markets[5], finding that it produces profits in 18 markets, and that those profits are significant in 10 markets. However, instead of dominating Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999), the strategies exist independently of each other. The profits do not reverse in the long run, nor are they overshadowed by alternative indicators, but are no longer significant in most markets if considering transaction costs.

Bornholt and Malin (2011) find, problematically for George and Hwang (2004), that the relative strength momentum is more profitable and robust than the 52-week strategy in 18 developed and 26 emerging market stock indices[6].

Importantly, Li and Yu (2012) use the Dow Jones 30-stock Industrial Average Index, from 1958 to 2009, to investigate psychological evidence on limited investor attention and anchoring. The authors propose two proxies for the degree to which investors under- and overreact to news, namely nearness to the 52-week high and to the historical high, finding that nearness to the 52-week high predicts positive future returns while nearness to the historical high predicts negative future returns. The proxies capture information not contained in macroeconomic factors, with results robust around G7 countries, and comparisons with NYSE/Amex confirm the findings. A possible justification, consistent with Griffin and Tversky (1992), is that the market underreacts to intermittent news, captured by the nearness to the 52-week high, and overreacts to a series of consistently positive (negative) news which would be the case for when it is closer (farther) to its historical high. Another explanation, developing on Tversky and Kahneman (1974), is that traders use both the 52-week high and the historical high as anchors, against which they evaluate the potential impact of news. In this case, nearness to the 52-week high would be prone to generating underreaction, as in George and Hwang (2004), while the representativeness bias would account for overreaction when prolonged good (bad) news pushes stock prices closer (farther) to the historical high.

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[5] Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Russia, Singapore, South Korea, Spain, Sweden, Switzerland, Taiwan, and UK.

[6] Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Czech Republic, Denmark, Egypt, France, Germany, Hong Kong, Hungary, India, Indonesia, Israel, Italy, Japan, Jordan, Malaysia, Mexico, Morocco, Netherlands, Norway, Pakistan, Peru, Philippines, Poland, Russia, Singapore, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Thailand, Turkey, UK, and US.

Bhootra and Hur (2013) find that, for a sample consisting of NYSE, AMEX, and NASDAQ stocks, from 1965 to 2008, that those stocks that have attained the 52-week price in the recent past significantly outperform those that have attained so in the distant past, and that conditioning on this factor increases the profitability of the strategy.

Finally, Raza *et al.* (2014) study the 52-week high strategy on the foreign exchange market, for 63 currencies, between 1997 and 2013, finding that the approach, contrary to relative strength, is not profitable in this market.

3. Implications for Asset Pricing Models

In the current section we start by presenting a literature review of the main asset pricing models, in subsection 3.1, and follow by addressing our view of the implications of George and Hwang (2004) concerning these models in subsection 3.2.

3.1. A Brief Overview of Relevant Asset Pricing Models

The present dissertation focuses on the impact of the momentum effect, and particularly of George and Hwang (2004)'s 52-week high strategy, on asset pricing models, specifically the problem of capturing the effect on a portfolio's excess returns. In order to provide the framework from which we arrive at our own model, we start by introducing a brief overview of previous relevant asset pricing models and the problems they face regarding the momentum effect.

The foundations of asset pricing theory can be found in the work of Markowitz (1952), whose theory of portfolio choice proposed that any asset or portfolio can be described by its mean, as a measure of return, and by its variance, as a measure of risk. The underlying intuition is that, in the assumption that investors are risk-adverse and have homogenous expectations, investors select mean-variance-efficient portfolios, understood as the combination of assets with the highest possible return for a given level of risk, or as the one with the lowest level of risk for any given return. The selection of a certain asset should be considered in accordance to its impact on the return and risk of the portfolio and, as long as the assets are not perfectly and positively correlated, diversification will lead to the reduction of the portfolio's risk.

The capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965), which marks the birth of and is still arguably the most widely used asset pricing model, develops on the work of Markowitz (1952) by adding two key assumptions: financial markets are efficient in the sense that there is perfect competition, there are no frictions and information is costless and received simultaneously by all agents; and there is the possibility of unlimited lending and borrowing at a risk-free rate. Black (1972) arrives at the same conclusion, even in the absence of unlimited borrowing and lending at a risk-free rate, as long as short selling is unrestricted.

The implication of the CAPM model is that, since increasing diversification leads to the eventual elimination of specific (firm) risk, investors shall be compensated only for the non-diversifiable systematic (market) risk, measured by the co-variation of the asset returns with the market returns as given by β, resulting in the by now familiar CAPM formula

$$\boldsymbol{E(R_i) = R_f + \left[E(R_M) - R_f\right]\beta_{iM}} \quad \textbf{(1)}$$

where $E(R_i)$ is the expected return on asset *i*, R_f is the risk-free rate, $E(R_M)$-R_f is the expected market risk-premium and β, given by $\frac{cov\,(R_i, R_M)}{\sigma^2(R_M)}$, is the measure of non-diversifiable risk.

Early on, Roll (1977) pointed out that the CAPM is a tautology, as the equation is satisfied by any mean-variance efficient portfolio, and that it is untestable as the market portfolio is unobservable since it is impossible to compute returns on all possible assets.

Problematically, the empirical tests of the CAPM also revealed several issues and insufficiencies of the model. The cross-sectional tests of Jensen *et al.* (1972) and Fama and French (1992), though confirming a positive relation between risk premium and betas, consistently find that, in the regressions, the intercept is greater than the risk-free rate and the slope is less than the risk premium. The time-series tests of Jensen *et al.* (1972) concurrently find positive alphas for assets with low betas and negative alphas for assets with high betas, while also observing that the relation between average returns and beta is too flat. Additionally, several studies find that considering other variables adds to the explanatory power of the CAPM: Basu (1977) finds that high E/P stocks have higher returns than expected according to the CAPM; Banz (1981) discovers the same effect on small cap stocks; Bhandari (1988) finds a similar anomaly on highly leveraged companies; Fama and French (1992) confirm that size, earnings-price, debt-to-equity and book-to-market ratios add to the explanatory power of the regressions. Finally, most importantly for our dissertation, the CAPM is also unable to explain anomalies such as the mean-reversion effect of De Bondt and Thaler (1985) and, particularly, the momentum effect of Jegadeesh and Titman (1993).

The limitations uncovered by the empirical tests of the CAPM, notwithstanding the model's continuing wide application in financial theory and practice, led to the development of more complicated and comprehensive models.

Fama and French (1993, 1996) propose a 3-factor model relying on the empirical finding that size and book-to-market equity capture variations in the cross-section of asset returns not explained by the betas. The model lacks a strong theoretical basis, being simply a construct born of empirical evidence, meant to capture the relation between the ratios and returns. As such the underlying reasoning for the size effect is left unexplained, though book-to-market equity may act as a proxy for relative distress, since weak firms with low earnings tend to have high BE/ME ratios while strong firms with persistent high earnings tend to exhibit low BE/ME ratios.

The factors explaining the return in excess of the R_f correspond to the excess return on the market portfolio (R_M - R_f); the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks (small minus big, SMB); and the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks (high minus low, HML).

The model formulation for the return of a given asset or portfolio is as follows

$$\boldsymbol{E(R_i) = R_f + b_{iM}[E(R_M) - R_f] + s_iE(SMB_t) + h_iE(HML_t)} \quad \textbf{(2)}$$

where $E(R_{Mt})$-R_{ft}, $E(SMB_t)$ and $E(HML_t)$ are the expected premiums of each risk factor and the loadings b_i, s_i and h_i, are the slopes in a time series regression.

Notwithstanding its theoretical limitations, the model captures much of the variation in cross-sections of average stock returns, as well as anomalies evidenced in empirical tests of the CAPM, and so the authors propose it may still be useful for both theoretical and practical applications. However, one important insufficiency of the 3-factor model, which the authors refer to as the main embarrassment to the model, is the failure to capture the momentum effect documented by Jegadeesh and Titman (1993).

In his work concerning persistence of mutual fund performance, Carhart (1997) discusses his own 4-factor model, which expands on the 3-factor model of Fama and French (1993, 1996) by adding a fourth factor that aims to capture the momentum anomaly. The 4-factor model is consistent with a model of market equilibrium with four risk factors but, alternatively, can be viewed as a performance attribution model comprising the mean return attributable to four different elementary strategies.

The 4-factor model is formulated as

$$\boldsymbol{E(R_i) = R_f + b_{iM}[E(R_M) - R_f] + s_iE(SMB_t) + h_iE(HML_t) + w_iE(WML_t)} \quad \textbf{(3)}$$

where $E(R_{Mt})$-R_{ft}, $E(SMB_t)$ and $E(HML_t)$ are the expected premiums on the factors proposed by Fama and French (1993, 1996), $E(WML_t)$ is the expected return on a portfolio mimicking the one-year momentum returns, and b_i, s_i, h_i and w_i correspond equally to the slopes in a time series regression.

The WML factor corresponds, specifically, to the equal-weight average of firms with the highest 30 percent eleven-month returns lagged one month minus the equal-weight average of firms with the lowest 30 percent eleven-month returns lagged one month, with the portfolios being reformed monthly.

Finally, we must mention the recent working paper by Fama and French (2014), proposing a 5-factor model, which adds profitability and investment risk factors to the 3-factor model. However, as the model does not directly address the momentum effect, we believe it does not take away the relevance of our own model.

3.2. Implications of George and Hwang (2004): A Proposal

The main purpose of the present dissertation is to propose and test a 4-factor model, in essence a variation of Carhart (1997)'s, based on a straightforward intuition, but that as far as we can tell has never been suggested in the literature.

As already stated, Fama and French (1993, 1996) identify the momentum effect as the greatest challenge to the 3-factor model and Carhart (1997) proposes adding a fourth risk factor, inspired by Jegadeesh and Titman (1993), to capture that anomaly.

However, if, as in George and Hwang (2004), the 52-week high strategy dominates all other main momentum strategies and, additionally, shows no signs of long-term reversal, it would be expected that a fourth risk factor constructed according to this strategy would better capture the momentum effect.

The formulation of the proposed 52W 4-factor model is thus closely related to that of Carhart (1997), being specified as

$$\boldsymbol{E(R_i) = R_f + b_{iM}[E(R_M) - R_f] + s_iE(SMB_t) + h_iE(HML_t) + m_iE(52W_t)} \quad (\mathbf{4})$$

substituting the previous E(WML_t) factor for the proposed E($52W_t$) factor, also aiming to capture the momentum effect, but with the new factor built according to George and Hwang (2004)'s 52-week high strategy.

The 52W factor, similarly to the value-weighted SMB and HML, and also to WML, will correspond to the monthly equal-weight average returns of the 30 percent firms with prices closest to their 52-week high minus the monthly equal-weight average returns of the 30 percent firms with prices farthest from their 52-week high.

The model is built on empirical foundations, and as such also lacks the theoretical basis of both the 3-factor and Carhart (1997)'s 4-factor model, but nonetheless, if successful, would add to the understanding of the factors governing stock returns. As in the previous empirical models, it can also be proposed that its eventual success in capturing the excess portfolio returns would mean it could still be useful in practical applications. Additionally, as the 52-week high effect is most probably the result of an anchor-and-adjust bias, it would contribute to the evidence of psychological effects playing a relevant role in the definition of stock prices.

In remainder of the dissertation we will build the 52W factor, and compare the results of the model in (4) with both the models in (2) and (3), for several portfolios, following the approach of Fama and French (2012).

4. Data and Methodology

Our approach follows closely the methodology Fama and French (2012) applied in the tests of the CAPM, 3-factor and Carhart (1997) 4-factor models in 23 countries (aggregated into 4 groups: North America, Japan, Europe and Asia Pacific).

In the present dissertation we proceed to compare our own 4-factor model to Fama and French (1993, 1996) and Carhart (1997)'s models', using data from the NYSE, NYSE MKT and NASDAQ stock markets, from January 1980 to December 2014, collected from DataStream and from Kenneth R French's website[1]. We should note that the inclusion of the 3-factor and Carhart (1997) 4-factor models' is to provide a benchmark against which to compare our own model, though it will nonetheless represent an update of Fama and French (1996). In Fama and French (2012) the authors group the US and Canada under the North America region and, as such, do not independently address the models' performance in the US market.

The tests comprise of time-series regressions of all models, seeking to capture the excess monthly return of a number of benchmark portfolios also retrieved from Kenneth R French's website, which we will next detail, following the ensuing formulations for

<u>Fama-French 3-factor model</u>:

$$\boldsymbol{R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB_t + h_i HML_t + \varepsilon_i} \quad (5)$$

<u>Carhart 4-factor model</u>:

$$\boldsymbol{R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB_t + h_i HML_t + w_i WML_t + \varepsilon_i} \quad (6)$$

<u>Proposed 52W 4-factor model</u>:

$$\boldsymbol{R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB_t + h_i HML_t + m_i 52W_t + \varepsilon_i} \quad (7)$$

where it will be expected that, if a given model is able to perfectly capture the excess monthly returns of a portfolio, the intercept α_i will be zero while the factor loadings will provide the relative contribution of each factor to the formation of those excess returns.

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1 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

The monthly returns of the R_M-R_f, SMB, HML and WML risk factors were all collected from Kenneth R. French's website. R_M-R_f corresponds to the value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, NYSE MKT, and NASDAQ that have a CRSP share code of 10 or 11 minus the one-month Treasury bill rate from Ibbotson Associates. The factors SMB and HML are constructed using 6 value-weighted portfolios formed on the intersections of 2 portfolios formed on size and 3 portfolios formed on book-to-market, SMB being the average return on the three small portfolios (value / neutral / growth) minus the average return on the three big portfolios (value / neutral / growth) and HML the average return on the two value portfolios (small / big) minus the average return on the two growth portfolios (small / big). We chose to use, for WML, the relative strength momentum factor available on the website which is built from 6 value-weighted portfolios formed on the intersections of 2 portfolios formed on size and 3 portfolios formed on prior *t*-12 to *t*-2 month returns, and corresponds to the monthly average return of the two high prior return portfolios minus the average return of the two low prior return portfolios.

In turn, our own 52W had to be constructed from raw daily data of the stocks listed on the NYSE, NYSE MKT and NASDAQ, collected from DataStream, using the Total Return Index (TRI) to adjust for stock splits, dividends and rights issues. In order to avoid survivorship bias we used all stocks, including dead and delisted, for the given period. However, and to assure the results were not influenced by small, illiquid and thinly traded stocks, following Jegadeesh and Titman (2001) we excluded stocks under $5 and additionally, if a stock was not traded during the previous month, it was not considered in the selection of the portfolios. At the beginning of each month *t* stocks were ranked according to the nearness to the 52-week high at the end of month *t*-2, since we skip a month between ranking and portfolio formation such as Fama and French (2012), given by $\frac{Price_{i,t-2}}{High_{i,t-2}}$, where $Price_{i,t-2}$ is the price of stock *i* at the end of month $t-2$ and $High_{i,t-2}$ is the highest price of stock *i* during the 12-month period that ends on the last day of month $t-2$. The 52W factor corresponds for each month *t*, to the equal-weighted returns of the winner portfolio, comprised of the top 30% ranking stocks, minus the equal-weighted returns of the loser portfolio constituted by the 30% worst ranking stocks. We should note that we follow George and Hwang (2004) in considering equal-weighted portfolios but, to increase comparison to the WML risk factor, we not only skip the month between ranking and portfolio formation but also do not consider overlapping holding periods.

In possession of all the inputs necessary to estimate the time-series regressions detailed in equations (5), (6) and (7), we then move on to test the explanatory power of all 3 models on the excess returns of a series of portfolios, closely following Fama and French (2012), with the data for the average returns of all the portfolios again retrieved, in its entirety, from Kenneth R. French's website. We start by comparing the 3 models' performance in explaining the average excess returns of the classic Fama and French (1993) 25 size-BE/ME portfolios of value-weighted NYSE, NYSE MKT, and NASDAQ stocks. The portfolios, constructed at the end of each June, correspond to the intersections of 5 portfolios formed on size (market equity, ME), and 5 portfolios formed on the ratio of book equity to market equity (BE/ME), using the NYSE quintiles. The underlying argument is that small stocks tend to have higher returns than big stocks, and high BE/ME stocks have higher returns than low BE/ME stocks, and so it is important to infer if the models capture those effects. Following, we test the 3 models on Fama and French (2012) 25 size-momentum portfolios of value-weighted NYSE, NYSE MKT, and NASDAQ stocks. The portfolios, constructed monthly, are the intersections of 5 portfolios formed on size (market equity, ME) and 5 portfolios formed on prior (12-2) return, using NYSE quintiles. It would be expected that it is in these portfolios that the inclusion of a momentum risk factor provides a clearer boost to the Fama and French (1993, 1996) 3-factor model, as the portfolios are built specifically to expose the momentum effect. Finally, as more thoroughly addressed over section 5, we find from our empirical observation that there is substantial difference in momentum premiums in subperiods 1980-2000 and 2001-2014, and particularly that 2009 seems to be an outlier year. As a result of this finding, we also conduct a subperiod analysis of the 25 size-momentum portfolios for these different time frames.

5. Main Findings

5.1. Summary Statistics

We begin by presenting the summary statistics for both the risk factors, in Table I, and the monthly percent excess returns of the 25 size-BE/ME and 25 size-momentum portfolios, in Tables II and III, for the period from January 1980 to December 2014.

Table I

Summary Statistics for the Risk Factors

R_M-R_f corresponds to the value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, NYSE MKT, and NASDAQ that have a CRSP share code of 10 or 11 minus the one-month Treasury bill rate from Ibbotson Associates. The factors SMB and HML are constructed using 6 value-weighted portfolios formed on the intersections of 2 portfolios formed on size and 3 portfolios formed on book-to-market, SMB being the average return on the three small portfolios (value / neutral / growth) minus the average return on the three big portfolios (value / neutral / growth) and HML the average return on the two value portfolios (small / big) minus the average return on the two growth portfolios (small / big). The risk factor WML is built from 6 value-weighted portfolios formed on the intersections of 2 portfolios formed on size and 3 portfolios formed on prior *t*-12 to *t*-2 month returns, and corresponds to the monthly average return of the two high prior return portfolios minus the average return of the two low prior return portfolios. Data for R_M-R_f, SMB, HML and WML risk factors were all collected from Kenneth R. French's website. 52W is a momentum factor built according to the 52-week high strategy, using all stocks listed on the NYSE, NYSE MKT and NASDAQ, collected from DataStream, excluding stocks under $5 and stocks not traded during the previous month, corresponding to the equal-weighted returns of the 30% top ranked stocks minus the equal-weighted returns of the 30% worst ranked stocks. Returns are calculated in simple monthly percent. Sample period is January 1980 to December 2014.

Risk Factors	Average Monthly Return	Std. Dev.	*t*-stat	Median Monthly Return	Cross-Correlations				
					R_M-R_f	SMB	HML	WML	52W
R_M-R_f	0.65	4.51	2.95	1.16	1.00	-	-	-	-
SMB	0.13	3.06	0.87	0.00	0.24	1.00	-	-	-
HML	0.30	3.03	2.04	0.27	-0.33	-0.31	1.00	-	-
WML	0.61	4.57	2.74	0.72	-0.12	0.06	-0.17	1.00	-
52W	0.12	3.86	0.65	0.50	-0.45	-0.34	0.26	0.68	1.00
WML (80-00)	0.97	3.82	4.03	1.05	0.21	0.26	-0.41	1.00	-
WML (01-14)	0.07	5.46	0.17	0.39	-0.48	-0.19	0.10	1.00	-
52W(80-00)	0.43	2.94	2.33	0.72	-0.28	-0.27	0.30	0.42	1.00
52W (01-14)	-0.34	4.90	-0.91	0.16	-0.64	-0.47	0.25	0.84	1.00

Concerning the risk factors, as shown above in Table I, it is clear that the market risk premium continues to be large in the US market at 0.65% per month, and also that the value premium is still a relevant 0.30% per month, but that the returns of the size premium are small and are not statistically significant. As regards the momentum effect, the competing factors WML and 52W show very different performances for the period. While WML has a high monthly return of 0.61% the 52W factor, problematically for our proposed model, achieves a modest and statistically insignificant 0.12% per month.

However Table I shows three additional aspects we must also consider, namely (i) the relatively low to moderate correlations between the proposed risk factors for the entire period, suggesting they are able to capture time-series variation (except for WML and 52W, somewhat in contradiction with George and Hwang (2004)'s assertion that these are separate momentum effects); (ii) that both WML and 52W have very different performances for the subperiods 1980-2000 and 2001-2014; and (iii) that correlations for the momentum risk factors also change substantially for the subperiods, concurrently indicating different abilities to explain the excess returns. Specifically, 52W achieves a statistically significant average return of 0.43% per month in the period from 1980 to 2000 (WML is an impressive 0.97%), very much in line with the results of George and Hwang (2004), but falls to a statistically insignificant average monthly return of -0.34% in the period from 2001 to 2014 (WML falls to an also statistically insignificant 0.07% per month). As already discussed, correlations between WML and 52W are significant for the entire sample, but increase impressively from 0.42 in 1980-2000 to 0.84 in 2001-2014. As such, our results are concordant with the finding of George and Hwang (2004) – whose sample period, we must again point out, is from 1963 to 2001 - that these are different effects up to 2000, but put them into question in the subsequent time-frame of 2001-2014 and for our whole period.

As more thoroughly addressed in subsection 5.3.3, it appears as though, in the more recent years, there seems to be no momentum effect in the US market but, when looking at monthly median returns, 52W achieves 0.50% for the whole period of 1980-2014 (WML 0.72%), 0.72% for the subperiod 1980-2000 (WML 1.05%), and 0.16% for the subperiod 2001-2014 (WML 0.39%). The underlying reason for the behavior of both 52W and WML seems to be related to more frequent periods of rapid inversion of market trends in the years of 2001-2014 appearing that, due to their reliance on the continuation of returns, it corresponds to periods in which momentum strategies appear to perform very negatively. In particular, both the returns for 52W and WML in the period are very affected by the impact of a single year, 2009, in which they respectively lose an astounding average of -4.18% and -5.43% per month. In subsection 5.3.3 we further discuss whether this apparent disappearance of momentum in the subperiod 2001-2014 corresponds to an effective absorption of the anomaly by the market, or if on the other hand it is primarily the result of an outlier year with a disproportionate impact due to the relatively reduced sample years – we should point out that from 2010 to 2014 the average return of WML is 0.36% per month, though 52W remains at only 0.05% per month, and both are statistically insignificant.

Turning to the benchmark portfolios, the interpretation of the excess returns of the 25 size-BE/ME portfolios, shown below in Table II, seems to be very much in line with the individual observations for the size (SMB) and value (HML) risk factors.

Table II

Summary Statistics for Monthly Percent Excess Returns on 25 Size-BE/ME Portfolios

The portfolios of NYSE, NYSE MKT and NASDAQ stocks, built each June, are the intersections of 5 portfolios formed on size (ME) and 5 portfolios formed on the ratio of book to market equity (BE/ME). The size breakpoints for year *t* are the NYSE market equity quintiles at the end of June of *t*. BE/ME for June of year *t* is the ratio of BE for the last fiscal year end in *t*-1 to ME for December of *t*-1. The BE/ME breakpoints are NYSE quintiles. R_f is the one-month Treasury bill rate at the beginning of the month *t*. All data from Kenneth R. French's website. Sample period is January 1980 to December 2014.

	Average					Standard Deviation				
	Growth	2	3	4	Value	Growth	2	3	4	Value
Small	0.08	0.84	0.89	1.02	1.10	7.90	6.70	5.61	5.26	5.65
2	0.49	0.80	1.00	0.97	0.94	7.11	5.77	5.16	5.10	5.80
3	0.62	0.87	0.86	0.90	1.13	6.60	5.39	4.92	4.87	5.19
4	0.80	0.76	0.79	0.84	0.88	5.96	5.17	5.15	4.67	5.19
Big	0.66	0.73	0.63	0.63	0.77	4.71	4.58	4.56	4.37	5.08

In particular, when analyzing the returns from the top to bottom rows, there seems to be no size effect for the lowest BE/ME quintile, with even an observed inverse size effect, though the size premium seems to apply in the remaining BE/ME quintiles, in line with the observed small average monthly return of SMB. On the other hand, the value effect seems very clear when analyzing the returns from the left to right columns, independently of the size quintile, noting however that the effect seems especially large in small caps, with an excess return of 1.10% per month.

As regards the excess returns of the 25 size-momentum portfolios, exhibited below in Panel A of Table III, the interpretation concerning the size effect is somewhat similar to that of the 25 size-BE/ME portfolios.

Table III

Summary Statistics for Monthly Percent Excess Returns on 25 Size-Momentum Portfolios

The portfolios of NYSE, NYSE MKT and NASDAQ stocks, constructed monthly, are the intersections of 5 portfolios formed on size (ME) and 5 portfolios formed on prior *t*-12 to *t*-2 returns (the strategy skips the sort month). The size breakpoints are the NYSE market equity quintiles. The monthly prior *t*-12 to *t*-2 return breakpoints are NYSE quintiles. R_f is the one-month Treasury bill rate at the beginning of the month *t*. All data from Kenneth R. French's website. Sample period is January 1980 to December 2014.

	Panel A: 1980-2014									
	Average					Standard Deviation				
	Loser	2	3	4	Winner	Loser	2	3	4	Winner
Small	-0.02	0.63	0.89	1.06	1.38	8.03	5.49	5.00	5.13	6.55
2	0.25	0.73	0.90	1.05	1.27	8.07	5.77	5.11	5.18	6.72
3	0.45	0.69	0.83	0.88	1.16	7.57	5.45	4.93	4.88	6.37
4	0.37	0.74	0.85	0.88	1.02	7.68	5.51	4.74	4.63	5.91
Big	0.42	0.67	0.52	0.73	0.85	7.05	4.89	4.35	4.34	5.34
	Panel B: 1980-2000									
	Average					Standard Deviation				
	Loser	2	3	4	Winner	Loser	2	3	4	Winner
Small	-0.70	0.42	0.75	0.94	1.45	6.51	4.82	4.65	5.02	6.82
2	-0.21	0.46	0.81	1.05	1.50	6.47	5.03	4.83	5.04	7.10
3	0.18	0.49	0.69	0.92	1.41	6.11	4.92	4.61	4.83	6.79
4	0.32	0.67	0.71	0.86	1.30	6.09	5.14	4.66	4.75	6.23
Big	0.57	0.79	0.53	0.83	1.04	5.87	4.48	4.44	4.60	5.79
	Panel C: 2001-2014									
	Average					Standard Deviation				
	Loser	2	3	4	Winner	Loser	2	3	4	Winner
Small	1.00	0.95	1.09	1.24	1.26	9.82	6.35	5.49	5.29	6.14
2	0.95	1.13	1.02	1.06	0.92	9.97	6.72	5.50	5.40	6.10
3	0.85	1.00	1.03	0.84	0.78	9.35	6.16	5.38	4.96	5.68
4	0.44	0.85	1.06	0.90	0.60	9.60	6.04	4.87	4.47	5.40
Big	0.19	0.50	0.50	0.57	0.58	8.54	5.46	4.21	3.91	4.59

Specifically, there seems to be an inverse size effect in the extreme loser quintile, and an inexistent size effect in the second momentum quintile, but the size premium appears to hold in the remaining quintiles. Momentum seems to be clearly present in all size quintiles, with an increasing trend in excess returns from the left (extreme loser) to the right (extreme winner) quintiles, again especially large in small caps.

Since we aim to address the performance of the models in capturing the momentum anomaly for subperiods 1980-2000 and 2001-2014, following the very different results for both WML and 52W, we also show the summary statistics of the 25 size-momentum portfolios for these subperiods. The results for subperiod 1980-2000, shown in Panel B of Table III, are qualitatively similar to those of the entire period but with significantly higher momentum spreads between the winner and loser quintiles, in line with the higher average returns of both WML and 52W. For the subperiod 2001-2014, shown in Panel C of Table III, however, the size effect makes an impressive comeback, with clearly higher returns for small caps, but the momentum effect, again concurrently with the disappointing returns of WML and 52W, is, at best, tenuous.

5.2. Asset Pricing Tests for the 25 size-BE/ME Portfolios

The results for the tests on the 25 size-BE/ME portfolios are presented in Table IV and consist of time-series regressions of the Fama and French (1993, 1996) 3-factor, Carhart (1997) 4-factor and 52W 4-factor models on those portfolios excess returns.

Analyzing the regressions α it seems that the Fama and French (1993, 1996) 3-factor model is able to capture most of the excess returns, with an average absolute α of 0.12%, although, concurrently with the existing literature, leaving significant unexplained returns in the lowest BE/ME quintile, both in the two smallest size and two biggest size quintiles, but especially a large negative return for low BE/ME microcaps stocks of around -0.69% per month. Additionally, the 3-factor model leaves a hint of the value effect on the smallest size quintile and creates a reverse value effect in the biggest size quintile. The explanation follows from the fact that value-growth spreads are larger for smaller stocks and the spreads in the HML loadings are not wider for these same smaller stocks. As a result, the model underestimates the value-growth spreads in microcaps while overestimating the spread for large caps (in the particular case of low BE/ME microcaps there seems to be an additional overestimation of the spread for the size effect). We should note that the average adjusted R^2 is 0.91.

Table IV

Regressions for Monthly Percent Excess Returns on 25 Size-BE/ME Portfolios (Jan. 1980 – Dec. 2014)

The table shows the results from time-series regressions of the Fama and French (1993, 1996) 3-factor model, Carhart (1997) 4-factor model and 52W 4-factor model on the monthly percent excess returns of the 25 portfolios created from 5 x 5 sorts on size and BE/ME. Reported are the individual α, risk factor loadings, respective HAC Newey-West *t*-statistics, adjusted R^2 and the regressions' standard errors. Sample period is January 1980 to December 2014.

Fama-French 3-Factor Model

$R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB + h_i HML + e_i$

	Growth	2	3	4	Value	Growth	2	3	4	Value
	α					t(α)				
Small	-0.69	0.05	0.10	0.19	0.13	-5.41	0.59	1.46	2.49	1.61
2	-0.24	-0.01	0.15	0.08	-0.13	-3.27	-0.07	2.11	1.04	-1.74
3	-0.03	0.05	0.01	0.01	0.16	-0.42	0.69	0.13	0.10	1.47
4	0.19	-0.04	-0.10	-0.01	-0.10	2.28	-0.39	-1.01	-0.08	-1.21
Big	0.18	0.09	-0.08	-0.16	-0.13	3.30	1.04	-0.93	-2.06	-1.09
Average |α|	0.12					-				
	b					t(b)				
Small	1.08	0.95	0.90	0.87	0.97	33.21	34.60	47.04	42.58	48.24
2	1.12	1.01	0.96	0.96	1.09	52.03	43.03	47.27	55.84	53.29
3	1.07	1.05	1.00	1.00	1.05	44.67	44.41	32.45	35.63	28.72
4	1.05	1.09	1.10	1.00	1.11	47.60	35.67	35.60	37.43	39.26
Big	0.95	1.01	1.01	0.98	1.07	56.61	38.93	40.43	50.38	26.42
	s					t(s)				
Small	1.31	1.28	1.04	0.99	1.03	22.83	16.50	30.57	31.28	25.95
2	0.95	0.85	0.74	0.73	0.89	23.94	15.15	14.01	17.18	21.12
3	0.73	0.51	0.42	0.39	0.47	23.26	6.44	5.53	6.41	6.13
4	0.42	0.20	0.18	0.20	0.16	9.54	2.72	2.34	5.46	2.92
Big	-0.26	-0.26	-0.23	-0.21	-0.13	-10.33	-5.98	-4.52	-5.88	-2.77

Carhart 4-Factor Model

$R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB + h_i HML + w_i WML + e_i$

	Growth	2	3	4	Value	Growth	2	3	4	Value
	α					t(α)				
Small	-0.62	0.05	0.09	0.17	0.17	-4.77	0.65	1.35	2.23	1.96
2	-0.18	0.02	0.15	0.08	-0.11	-2.77	0.26	2.38	1.08	-1.50
3	0.01	0.09	0.02	0.02	0.20	0.18	1.02	0.27	0.24	1.77
4	0.19	-0.02	-0.04	0.01	-0.05	2.42	-0.19	-0.44	0.16	-0.62
Big	0.20	0.06	-0.09	-0.13	-0.08	3.64	0.72	-1.00	-1.69	-0.70
Average |α|	0.11					-				
	b					t(b)				
Small	1.07	0.95	0.90	0.87	0.96	32.73	37.53	49.18	41.41	44.60
2	1.10	1.00	0.96	0.96	1.09	58.62	45.00	47.87	57.29	53.46
3	1.06	1.05	1.00	1.00	1.04	43.37	44.01	34.08	35.21	29.83
4	1.05	1.08	1.09	0.99	1.10	47.09	35.93	35.57	36.12	42.47
Big	0.94	1.01	1.01	0.97	1.06	54.26	42.29	37.01	51.36	25.96
	s					t(s)				
Small	1.31	1.28	1.04	0.99	1.03	21.10	16.65	31.51	30.51	28.27
2	0.96	0.85	0.74	0.73	0.89	28.11	16.25	14.44	17.45	21.80
3	0.73	0.51	0.42	0.39	0.47	24.6	6.93	5.73	6.68	6.65
4	0.42	0.20	0.19	0.20	0.17	9.67	2.88	2.65	5.55	3.39
Big	-0.26	-0.26	-0.23	-0.21	-0.13	-10.76	-5.79	-4.48	-6.46	-2.67

52W 4-Factor Model

$R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB + h_i HML + m_i 52W + e_i$

	Growth	2	3	4	Value	Growth	2	3	4	Value
	α					t(α)				
Small	-0.62	0.06	0.08	0.20	0.16	-4.88	0.71	1.28	2.37	1.79
2	-0.21	-0.01	0.13	0.06	-0.13	-3.13	-0.12	1.99	0.90	-1.70
3	-0.02	0.05	0.00	0.00	0.18	-0.21	0.64	0.00	0.03	1.64
4	0.19	-0.04	-0.10	-0.01	-0.08	2.36	-0.44	-1.01	-0.13	-0.99
Big	0.18	0.06	-0.09	-0.15	-0.09	3.32	0.70	-1.04	-2.07	-0.78
Average |α|	0.12					-				
	b					t(b)				
Small	1.02	0.95	0.91	0.87	0.95	29.17	41.03	52.44	36.82	37.05
2	1.09	1.01	0.98	0.98	1.09	56.07	49.84	46.67	52.99	50.06
3	1.05	1.06	1.01	1.01	1.03	39.25	40.62	33.31	30.59	31.67
4	1.05	1.09	1.11	1.00	1.09	43.33	37.19	34.54	32.12	40.75
Big	0.95	1.03	1.02	0.97	1.03	51.70	38.74	34.79	48.88	26.60
	s					t(s)				
Small	1.25	1.28	1.05	0.99	1.01	15.75	14.03	33.14	31.21	31.61
2	0.93	0.85	0.76	0.75	0.89	25.98	13.36	11.08	13.77	20.84
3	0.71	0.52	0.43	0.40	0.45	21.86	5.76	4.69	5.46	6.01
4	0.42	0.21	0.18	0.20	0.15	8.11	2.32	2.12	5.34	2.82
Big	-0.27	-0.23	-0.22	-0.22	-0.17	-9.66	-4.56	-4.42	-5.49	-2.74

	h					t(h)					h					t(h)					h					t(h)				
Small	-0.35	0.01	0.24	0.44	0.67	-6.12	0.09	6.84	13.33	18.57	-0.37	0.01	0.24	0.46	0.65	-6.20	0.09	6.97	13.01	17.78	-0.33	0.06	0.24	0.44	0.68	-5.27	0.11	7.85	13.43	19.77
2	-0.38	0.14	0.42	0.57	0.84	-8.43	2.13	7.39	11.04	24.35	-0.41	0.13	0.42	0.57	0.83	-8.42	1.84	7.01	11.75	23.32	-0.37	0.14	0.42	0.57	0.84	-7.83	2.18	7.53	10.84	24.38
3	-0.46	0.21	0.47	0.63	0.76	-14.61	3.13	6.20	8.02	12.06	-0.47	0.20	0.46	0.63	0.75	-16.22	2.90	5.94	7.54	12.68	-0.45	0.21	0.46	0.64	0.77	-15.01	3.09	6.22	8.11	12.01
4	-0.42	0.23	0.48	0.56	0.80	-10.64	2.72	5.89	8.81	15.90	-0.42	0.22	0.46	0.55	0.78	-11.44	2.50	5.10	7.77	14.62	-0.42	0.23	0.48	0.56	0.80	-10.33	2.73	5.97	9.13	15.76
Big	-0.35	0.09	0.29	0.60	0.74	-11.03	1.47	5.04	11.92	11.56	-0.36	0.10	0.29	0.59	0.71	-11.38	1.83	5.72	11.08	10.24	-0.35	0.08	0.28	0.60	0.75	-10.89	1.47	5.01	12.05	11.64
	w					t(w)					w					t(w)					w					t(w)				
Small	-	-	-	-	-	-	-	-	-	-	-0.08	0.00	0.01	0.03	-0.04	-1.38	-0.04	0.59	1.19	-1.84	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-	-0.07	-0.03	-0.01	0.00	-0.01	-2.70	-0.96	-0.19	-0.02	-0.69	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-	-0.05	-0.04	-0.01	-0.02	-0.05	-2.48	-0.87	-0.35	-0.34	-1.23	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-	0.00	-0.03	-0.07	-0.02	-0.06	0.07	-0.61	-1.54	-0.66	-1.82	-	-	-	-	-	-	-	-	-	-
Big	-	-	-	-	-	-	-	-	-	-	-0.02	0.03	0.04	-0.04	-0.06	-0.91	1.14	0.12	-1.37	-1.78	-	-	-	-	-	-	-	-	-	-
	m					t(m)					m					t(m)					m					t(m)				
Small	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.20	-0.01	0.05	0.01	-0.07	-3.07	-0.26	1.56	0.42	-2.09
2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.09	0.01	0.04	0.04	0.00	-2.54	0.22	0.88	0.96	0.07
3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.04	0.01	0.04	0.02	-0.05	-1.91	0.21	0.67	0.30	-1.11
4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.01	0.01	0.01	0.01	-0.06	0.11	0.12	0.09	0.27	-1.31
Big	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.00	0.08	0.02	-0.01	-0.13	-0.15	2.50	0.66	-0.31	-2.38
	R^2					s(e)					R^2					s(e)					R^2					s(e)				
Small	0.90	0.93	0.94	0.93	0.93	2.45	1.77	1.33	1.40	1.47	0.91	0.93	0.94	0.93	0.93	2.43	1.77	1.33	1.40	1.46	0.91	0.93	0.94	0.93	0.93	2.36	1.77	1.32	1.40	1.45
2	0.95	0.94	0.93	0.93	0.94	1.52	1.46	1.34	1.39	1.40	0.96	0.94	0.93	0.93	0.94	1.49	1.46	1.35	1.40	1.40	0.96	0.94	0.93	0.93	0.94	1.49	1.46	1.34	1.39	1.40
3	0.95	0.90	0.88	0.88	0.88	1.50	1.71	1.68	1.69	1.86	0.95	0.90	0.88	0.88	0.87	1.48	1.71	1.68	1.69	1.85	0.95	0.90	0.88	0.88	0.87	1.49	1.72	1.68	1.69	1.85
4	0.94	0.88	0.87	0.87	0.87	1.50	1.76	1.86	1.69	1.87	0.94	0.88	0.87	0.87	0.87	1.50	1.76	1.84	1.69	1.85	0.94	0.88	0.87	0.87	0.87	1.50	1.77	1.87	1.69	1.86
Big	0.95	0.89	0.87	0.89	0.80	1.10	1.49	1.67	1.45	2.27	0.95	0.90	0.87	0.89	0.80	1.10	1.48	1.67	1.45	2.25	0.95	0.90	0.87	0.89	0.81	1.11	1.47	1.67	1.46	2.23
Average R^2	0.91					-					0.91					-					0.91					-				

Adding a momentum factor, be it either WML or 52W, seems no have virtually no effect in the power of the regressions on the excess returns on the 25 size-BE/ME portfolios, with the inclusion of WML reducing the average absolute α from 0.12% to 0.11%, while the inclusion of 52W has no impact on the average absolute α. Unsurprisingly, the loadings for the WML or the 52W factors are very small and mostly statistically insignificant, while the impact on the adjusted R^2 is irrelevant.

We must stress, however, that the portfolios are constructed according to the empirically observed size and value anomalies, and the Fama and French (1993, 1996) 3 factor model is built to specifically capture those effects.

A more relevant test of the momentum factors is presented in the next subsection when we address their power on the excess returns of the 25 size-momentum portfolios.

5.3. Asset Pricing Tests for the 25 Size-Momentum Portfolios

Aiming to assert the models' ability to capture the momentum anomaly, as shown below in Table V, we proceed with regressions of the 3-factor, Carhart (1997) 4-factor and 52W 4-factor models on the excess returns of the 25 size-momentum portfolios.

The Fama and French (1993, 1996) 3-factor model fares much worse on these portfolios, with a high average absolute α of 0.31%, while estimating strongly negative intercepts for past short-term losers and high positive intercepts for short-term winners, with an average adjusted R^2 of only 0.82. The problem is that past losers load more on R_M-R_f and HML than past winners, and as such the model predicts the reversal of future returns for both losers and winners, missing the short-term continuation of the returns.

In this case, introducing a momentum factor, WML or 52W, clearly improves the regressions power, significantly reducing the average absolute α while also providing a boost to the average adjusted R^2. Our aim is to compare the impact of both factors.

The results for the Carhart (1997) 4-factor model show a decrease of the average absolute α to 0.14% and an improvement of the average adjusted R^2 to 0.90. However there are still clearly traces of the momentum effect on the two lowest size quintiles, the greatest problem being the high negative intercept of the microcaps' losers (-0.45%), while the model also creates a mild reverse momentum effect for large caps.

Table V

Regressions for Monthly Percent Excess Returns on 25 Size-Momentum Portfolios (Jan. 1980 – Dec. 2014)

The table shows the results from time-series regressions of the Fama and French (1993, 1996) 3-factor model, Carhart (1997) 4-factor model and 52W 4-factor model on the monthly percent excess returns of the 25 portfolios created from 5 x 5 sorts on size and momentum. Reported are the individual α, risk factor loadings, respective HAC Newey-West *t*-statistics, adjusted R^2 and the regressions' standard errors. Sample period is January 1980 to December 2014.

Fama-French 3-Factor Model

$R_i - R_f = \alpha_i + b_i(R_M-R_f) + s_iSMB + h_iHML + e_i$

	Loser	2	3	4	Winner	Loser	2	3	4	Winner
	α					t(α)				
Small	-1.08	-0.24	0.08	0.29	0.57	-5.74	-2.36	0.94	3.19	4.01
2	-0.86	-0.19	0.07	0.25	0.45	-4.70	-1.72	0.86	3.46	4.42
3	-0.57	-0.18	0.00	0.09	0.39	-2.85	-1.56	-0.02	0.93	3.70
4	-0.66	-0.14	0.07	0.15	0.34	-2.94	-1.23	0.63	1.72	2.71
Big	-0.48	-0.04	-0.13	0.12	0.28	-2.10	-0.30	-1.63	1.42	2.50
Average |α|	0.31					-				
	b					t(b)				
Small	1.24	0.95	0.88	0.86	0.98	14.90	26.22	34.08	27.29	26.83
2	1.37	1.06	0.96	0.94	1.07	14.31	27.36	37.70	34.25	33.73
3	1.33	1.09	0.99	0.98	1.07	13.98	26.27	39.09	28.18	30.26
4	1.38	1.14	1.02	0.98	1.02	13.13	28.72	32.38	30.27	22.08
Big	1.30	1.00	0.96	0.94	0.99	12.81	21.23	35.25	30.10	22.09
	s					t(s)				
Small	1.13	0.87	0.78	0.85	1.10	7.50	9.16	9.19	14.23	19.19
2	0.94	0.75	0.64	0.74	1.00	6.58	6.54	7.62	10.39	21.67
3	0.55	0.41	0.44	0.41	0.75	3.26	3.49	5.26	5.04	17.24
4	0.29	0.13	0.10	0.10	0.47	1.92	1.27	0.98	1.29	6.20
Big	-0.16	-0.21	-0.24	-0.25	-0.06	-1.34	-3.41	-6.16	-6.98	-1.06

Carhart 4-Factor Model

$R_i - R_f = \alpha_i + b_i(R_M-R_f) + s_iSMB + h_iHML + w_iWML + e_i$

	Loser	2	3	4	Winner	Loser	2	3	4	Winner
	α					t(α)				
Small	-0.45	-0.03	0.13	0.24	0.36	-2.96	-0.42	1.71	2.47	2.78
2	-0.20	0.08	0.12	0.21	0.19	-1.72	0.91	1.42	2.64	2.24
3	0.10	0.08	0.11	0.01	0.08	0.82	0.86	1.24	0.12	1.00
4	0.07	0.18	0.18	0.07	-0.03	0.55	1.97	1.85	0.81	-0.24
Big	0.18	0.32	-0.05	-0.03	-0.10	1.03	3.79	-0.63	-0.32	-1.26
Average |α|	0.14					-				
	b					t(b)				
Small	1.08	0.89	0.87	0.87	1.04	30.69	35.73	34.09	29.35	35.95
2	1.21	0.99	0.95	0.95	1.14	42.47	51.86	38.23	40.70	45.21
3	1.17	1.02	0.96	1.00	1.15	26.96	36.81	41.90	32.11	61.49
4	1.20	1.07	0.99	1.00	1.11	26.66	41.36	31.68	38.00	34.52
Big	1.13	0.91	0.94	0.97	1.09	20.95	46.35	37.64	38.87	44.91
	s					t(s)				
Small	1.17	0.89	0.79	0.85	1.09	16.32	13.77	10.25	13.31	17.75
2	0.98	0.76	0.65	0.74	0.98	21.28	10.45	8.45	9.70	23.57
3	0.59	0.43	0.44	0.41	0.73	8.70	5.50	6.83	4.52	18.19
4	0.34	0.15	0.10	0.10	0.45	7.16	2.61	1.29	1.12	12.43
Big	-0.11	-0.19	-0.24	-0.26	-0.09	-2.14	-6.94	-6.69	-7.53	-2.29

52W 4-Factor Model

$R_i - R_f = \alpha_i + b_i(R_M-R_f) + s_iSMB + h_iHML + m_i52W + e_i$

	Loser	2	3	4	Winner	Loser	2	3	4	Winner
	α					t(α)				
Small	-0.75	-0.14	0.10	0.26	0.50	-4.38	-1.47	1.22	2.84	3.59
2	-0.55	-0.07	0.08	0.22	0.35	-4.29	-0.80	0.92	3.04	3.44
3	-0.24	-0.08	0.03	0.04	0.25	-1.90	-0.74	0.33	0.40	2.56
4	-0.32	-0.02	0.11	0.10	0.17	-1.91	-0.21	1.02	1.16	1.44
Big	-0.20	0.10	-0.10	0.05	0.14	-0.93	0.99	-1.23	0.66	1.41
Average |α|	0.20					-				
	b					t(b)				
Small	0.93	0.86	0.86	0.88	1.05	16.32	26.17	28.79	25.68	32.27
2	1.08	0.95	0.96	0.97	1.17	30.61	39.84	39.58	43.19	43.56
3	1.03	0.99	0.96	1.02	1.20	24.24	31.91	42.63	30.64	43.96
4	1.06	1.03	0.98	1.03	1.17	18.41	30.74	31.57	42.33	29.33
Big	1.04	0.87	0.93	1.00	1.13	12.92	29.56	35.83	32.86	32.58
	s					t(s)				
Small	0.85	0.79	0.76	0.87	1.17	12.26	11.53	8.60	12.21	18.90
2	0.67	0.65	0.64	0.77	1.09	10.22	8.29	6.66	8.13	18.43
3	0.28	0.32	0.41	0.45	0.87	3.97	3.84	5.09	3.94	15.73
4	0.00	0.03	0.06	0.14	0.61	0.06	0.49	0.67	1.31	17.28
Big	-0.39	-0.33	-0.26	-0.20	0.06	-4.34	-7.86	-7.26	-4.12	1.08

	h					t(h)					h					t(h)					h					t(h)				
Small	0.35	0.50	0.45	0.33	0.06	2.14	6.89	7.97	5.36	0.89	0.09	0.41	0.43	0.35	0.15	1.20	7.23	8.70	5.94	2.91	0.42	0.52	0.46	0.33	0.05	5.50	8.08	7.95	5.21	0.79
2	0.33	0.45	0.38	0.30	-0.06	1.96	5.10	5.62	5.47	-0.95	0.06	0.34	0.36	0.32	0.05	1.36	5.36	5.46	6.80	1.73	0.40	0.48	0.38	0.29	-0.08	4.19	6.18	5.52	5.12	-1.87
3	0.27	0.40	0.43	0.36	-0.10	1.64	4.91	6.15	5.25	-1.25	-0.01	0.29	0.38	0.39	0.03	-0.10	4.55	5.92	6.04	0.77	0.34	0.42	0.43	0.35	-0.13	4.32	6.05	6.23	4.93	-2.87
4	0.33	0.41	0.36	0.26	-0.13	1.99	4.89	4.73	3.54	-1.40	0.03	0.28	0.32	0.29	0.02	0.56	4.15	4.25	4.41	0.44	0.40	0.44	0.37	0.25	-0.16	4.71	6.00	4.85	3.49	-3.14
Big	0.25	0.28	0.18	0.11	-0.22	1.47	3.41	4.13	1.96	-2.54	-0.03	0.14	0.15	0.17	-0.06	-0.43	3.16	4.21	4.09	-1.49	0.30	0.31	0.19	0.09	-0.25	2.95	5.13	4.45	1.91	-4.15

	w					t(w)					w					t(w)					w					t(w)				
Small	-	-	-	-	-	-	-	-	-	-	-0.74	-0.25	-0.06	0.06	0.26	-10.01	-7.08	-1.87	1.49	6.52	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-	-0.78	-0.32	-0.06	0.06	0.32	-11.96	-7.33	-1.54	1.69	14.62	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-	-0.79	-0.32	-0.14	0.09	0.37	-22.43	-9.90	-3.68	1.85	12.84	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-	-0.87	-0.37	-0.14	0.09	0.43	-21.53	-9.00	-3.83	2.61	13.10	-	-	-	-	-	-	-	-	-	-
Big	-	-	-	-	-	-	-	-	-	-	-0.79	-0.42	-0.09	0.17	0.46	-17.69	-12.46	-2.25	5.25	11.28	-	-	-	-	-	-	-	-	-	-

	m					t(m)					m					t(m)					m					t(m)				
Small	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.94	-0.28	-0.07	0.07	0.21	-7.54	-4.94	-1.23	1.31	3.75
2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.91	-0.34	-0.01	0.09	0.29	-7.64	-5.64	-0.21	1.84	5.39
3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.94	-0.30	-0.10	0.14	0.40	-11.07	-6.59	-1.80	2.01	7.88
4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.97	-0.34	-0.11	0.14	0.48	-9.56	-5.74	-2.23	2.45	9.87
Big	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-0.80	-0.40	-0.08	0.18	0.42	-8.30	-7.46	-1.62	4.48	7.83

	R^2					s(e)					R^2					s(e)					R^2					s(e)				
Small	0.73	0.87	0.89	0.89	0.87	4.20	1.98	1.63	1.69	2.36	0.89	0.91	0.90	0.89	0.90	2.65	1.66	1.61	1.68	2.06	0.88	0.90	0.89	0.89	0.88	2.82	1.76	1.62	1.68	2.25
2	0.77	0.86	0.90	0.92	0.90	3.90	2.15	1.63	1.45	2.08	0.95	0.92	0.90	0.92	0.95	1.80	1.61	1.61	1.43	1.50	0.91	0.90	0.90	0.93	0.93	2.46	1.84	1.63	1.42	1.84
3	0.70	0.84	0.88	0.87	0.87	4.15	2.17	1.72	1.75	2.28	0.91	0.91	0.89	0.88	0.94	2.21	1.66	1.61	1.71	1.58	0.87	0.88	0.88	0.88	0.92	2.74	1.92	1.69	1.68	1.84
4	0.64	0.81	0.86	0.87	0.80	4.58	2.41	1.75	1.70	2.61	0.89	0.90	0.88	0.87	0.91	2.51	1.75	1.65	1.65	1.79	0.82	0.85	0.87	0.88	0.88	3.26	2.13	1.72	1.64	2.08
Big	0.62	0.75	0.88	0.86	0.77	4.36	2.47	1.49	1.61	2.57	0.86	0.89	0.89	0.89	0.91	2.63	1.61	1.45	1.42	1.58	0.76	0.82	0.89	0.88	0.84	3.46	2.09	1.47	1.49	2.15
Average R^2	0.82					-					0.90					-					0.88					-				

The question is that, as previously shown in Table III, and addressed in subsection 5.1, the momentum returns are greater for small caps than for large caps, while the spreads in the WML factor loadings, from losers to winners, are at least as large for the biggest size quintiles as for the smallest size quintiles.

Our own 52W 4-factor model also corresponds to an improvement relative to the 3-factor model, but less so than the Carhart (1997) 4-factor model, reducing the average α to a still economically relevant 0.20% and improving the average adjusted R^2 to 0.88. The intercepts for the short-term losers remain strongly negative, once again the microcap losers being the greatest problem with -0.75%, and the intercepts for short-term winners, especially in the three smaller size quintiles, remain strongly positive. The issue is that besides having similar, but less severe, difficulties as the Carhart (1997) 4-factor model in capturing the different momentum spreads for the distinct size quintiles, the loadings on the HML factor continue to predict a reversal of the future returns. The results indicate that the 52W factor is not able to capture the momentum effect as well as the WML factor, leaving the overall performance of the 52W 4-factor model somewhere between the 3-factor model and the Carhart (1997) 4-factor model.

On one hand, the results are not surprising, considering the summary statistics shown in Table I for WML and 52W, with WML exhibiting far larger average returns and variance, indicating a greater capacity to explain the portfolios' excess returns. However, on the other hand, we must also take into account that since the portfolios are built on Jegadeesh and Titman (1993) momentum, they are also somewhat tilted towards the excess returns being better explained by the WML factor.

Since the subperiod analysis shows very different average premiums for both WML and 52W, in the periods 1980-2000 and 2001-2014, we repeat the test for the 25 size-momentum portfolios for these smaller subsamples.

5.3.1. Asset Pricing Tests for the 25 Size-Momentum Portfolios (1980-2000)

We start by looking at the subperiod 1980-2000, with the results for all the models presented in Table VI, concluding that the issues for all the 3 models are qualitatively similar to those in the entire period 1980-2014, although they appear to be greatly magnified. This probably results from the combined effect that momentum returns are much larger during this subperiod and, concurrently, the sample period is much smaller.

The regressions on the Fama and French (1993, 1996) 3-factor model show overall large α, corresponding to an average absolute of 0.42%, with especially large negative intercepts in short-term losers, and large positive intercepts in past winners. Again the factor loadings in HML, and also very slightly on R_M-R_f, continue to be larger for past losers than for past winners, erroneously predicting the future reversal of returns. The average adjusted R^2, as for the entire period, is 0.82.

The Carhart (1997) 4-factor model once again corresponds to a vast improvement relative to the 3-factor model, reducing the overall average absolute α to 0.22% while increasing the average adjusted R^2 to 0.89. However, not only does the model not capture the momentum effect on small caps, with large negative intercepts for small cap losers and large positive intercepts for small cap winners, it also creates a very significant reverse momentum effect for large caps. Succinctly, the problems already observed for the entire period, shown in Table V, also apply in the subperiod 1980-2000. However, the spreads in the WML factor loadings, from losers to winners, are now even larger for the biggest size than smallest size quintiles exacerbating the issue.

Moving on to the 52W 4-factor model, Table VI below shows that, as occurs for the entire period, the performance of our model in capturing the momentum effect lies somewhere between the Fama and French (1993, 1996) 3-factor and Carhart (1997) 4-factor models. The average absolute α is 0.30%, still very high despite a clear advance relative to the 3-factor model, and clearly worse than the 0.22% of the Carhart (1997) 4-factor model. The average adjusted R^2 improves slightly to 0.85. The problems with the intercepts correspond mostly, but not exclusively, to large negative intercepts in almost all short-term losers size quintiles, and generally large positive intercepts for short-term winners. Once again the spreads in the 52W factor fail to account for the different momentum returns for each size quintile. Additionally, the loadings on the HML factor continue to predict a future, though unobserved, reversion of the returns.

In summary, notwithstanding the fact that the performance of all models is worse for the subperiod of 1980-2000, the conclusions are similar to those of the entire period.

Table VI

Regressions for Monthly Percent Excess Returns on 25 Size-Momentum Portfolios (Jan. 1980 – Dec. 2000)

The table shows the results from time-series regressions of the Fama and French (1993, 1996) 3-factor model, Carhart (1997) 4-factor model and 52W 4-factor model on the monthly percent excess returns of the 25 portfolios created from 5 x 5 sorts on size and momentum. Reported are the individual α, risk factor loadings, respective HAC Newey-West *t*-statistics, adjusted R^2 and the regressions' standard errors. Sample period is January 1980 to December 2000.

Fama-French 3-Factor Model

$R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB + h_i HML + e_i$

	Loser	2	3	4	Winner	Loser	2	3	4	Winner
	α					t(α)				
Small	-1.59	-0.39	-0.05	0.12	0.70	-8.58	-3.12	-0.44	1.13	3.95
2	-1.17	-0.43	-0.07	0.19	0.71	-5.53	-3.10	-0.64	1.80	5.73
3	-0.80	-0.47	-0.25	-0.02	0.59	-3.29	-3.31	-2.00	-0.21	5.26
4	-0.70	-0.37	-0.26	-0.08	0.57	-2.34	-2.42	-2.25	-0.79	4.41
Big	-0.35	-0.02	-0.30	0.02	0.31	-1.30	-0.13	-3.03	0.18	2.27
Average |α|	0.42					-				
	b					t(b)				
Small	1.06	0.90	0.89	0.92	1.02	19.44	25.57	23.08	25.12	23.62
2	1.17	1.00	1.00	1.00	1.11	16.79	24.78	30.55	28.60	32.22
3	1.15	1.06	1.02	1.05	1.14	12.15	19.60	35.05	23.03	32.75
4	1.15	1.14	1.07	1.08	1.06	9.79	20.80	26.13	35.10	24.36
Big	1.07	0.91	0.99	1.00	1.06	11.03	15.83	31.03	36.72	20.44
	s					t(s)				
Small	0.99	0.78	0.73	0.85	1.12	6.32	7.77	7.50	12.74	16.17
2	0.78	0.64	0.55	0.69	1.02	5.76	5.59	7.02	9.50	20.73
3	0.42	0.36	0.40	0.40	0.79	2.39	2.86	4.91	4.38	17.95
4	0.20	0.08	0.04	0.07	0.50	1.31	0.73	0.41	0.80	6.49
Big	-0.15	-0.24	-0.28	-0.32	-0.11	-1.05	-3.21	-6.44	-7.66	-1.62

Carhart 4-Factor Model

$R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB + h_i HML + w_i WML + e_i$

	Loser	2	3	4	Winner	Loser	2	3	4	Winner
	α					t(α)				
Small	-0.97	-0.09	0.09	0.10	0.43	-6.18	-0.76	0.77	0.76	2.78
2	-0.43	-0.04	0.10	0.18	0.37	-3.62	-0.41	0.86	1.48	3.29
3	0.02	-0.05	-0.04	-0.04	0.24	0.15	-0.41	-0.29	-0.26	2.26
4	0.24	0.19	0.01	-0.09	0.14	1.35	1.50	0.08	-0.79	1.14
Big	0.62	0.57	-0.12	-0.13	-0.24	3.45	4.43	-1.25	-1.45	-2.66
Average |α|	0.22					-				
	b					t(b)				
Small	1.06	0.90	0.89	0.92	1.02	27.09	27.56	21.84	25.75	27.07
2	1.17	1.00	1.00	1.00	1.11	42.71	35.33	28.81	28.70	29.50
3	1.15	1.06	1.02	1.05	1.14	21.37	30.80	37.87	23.10	42.57
4	1.16	1.14	1.08	1.08	1.06	17.54	38.66	33.36	34.97	33.89
Big	1.07	0.92	0.99	1.00	1.06	22.81	30.47	32.78	43.30	37.45
	s					t(s)				
Small	1.05	0.81	0.75	0.84	1.09	11.06	12.37	9.35	12.99	13.48
2	0.85	0.68	0.57	0.69	0.98	16.90	9.83	9.44	9.96	16.65
3	0.51	0.40	0.42	0.40	0.75	6.52	5.23	7.24	4.59	15.13
4	0.30	0.14	0.07	0.07	0.45	5.71	2.99	1.07	0.83	10.12
Big	-0.04	-0.18	-0.26	-0.34	-0.17	-0.80	-4.56	-5.87	-9.10	-4.05

52W 4-Factor Model

$R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB + h_i HML + m_i 52W + e_i$

	Loser	2	3	4	Winner	Loser	2	3	4	Winner
	α					t(α)				
Small	-1.25	-0.24	0.02	0.11	0.65	-5.64	-1.73	0.16	0.89	3.47
2	-0.85	-0.28	-0.04	0.16	0.63	-4.99	-2.21	-0.41	1.46	4.24
3	-0.46	-0.34	-0.20	-0.07	0.45	-2.38	-2.56	-1.65	-0.50	3.89
4	-0.35	-0.21	-0.19	-0.11	0.38	-1.36	-1.38	-1.58	-1.11	2.84
Big	-0.01	0.17	-0.23	-0.04	0.15	-0.05	1.04	-2.21	-0.50	1.25
Average |α|	0.30					-				
	b					t(b)				
Small	0.98	0.86	0.87	0.93	1.04	18.81	21.88	19.95	24.68	24.77
2	1.09	0.96	1.00	1.00	1.13	25.17	28.91	29.51	31.51	32.18
3	1.07	1.03	1.01	1.06	1.17	17.01	24.75	38.29	24.44	35.46
4	1.07	1.10	1.06	1.09	1.10	12.57	23.43	28.28	39.36	28.04
Big	0.98	0.86	0.97	1.12	1.10	14.81	20.30	29.69	40.28	24.27
	s					t(s)				
Small	0.88	0.73	0.71	0.85	1.14	11.03	11.90	8.26	11.88	14.93
2	0.67	0.59	0.54	0.70	1.05	10.06	7.76	6.74	7.97	16.10
3	0.31	0.31	0.38	0.42	0.83	3.36	3.38	4.97	3.71	14.57
4	0.08	0.02	0.01	0.08	0.56	0.84	0.34	0.17	0.79	14.32
Big	-0.26	-0.31	-0.30	-0.30	-0.06	-2.80	-5.04	-8.10	-8.27	-1.16

	h					t(h)				
Small	0.32	0.46	0.44	0.39	0.01	2.15	5.45	6.09	5.43	0.06
2	0.26	0.43	0.38	0.33	-0.13	2.09	4.20	4.68	5.04	-2.07
3	0.29	0.47	0.51	0.43	-0.14	2.05	4.68	5.88	4.80	-2.07
4	0.40	0.51	0.46	0.32	-0.23	2.90	4.83	4.83	4.09	-2.66
Big	0.27	0.29	0.18	0.08	-0.32	1.79	2.77	3.00	1.17	-3.31
	w					t(w)				
Small	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-
Big	-	-	-	-	-	-	-	-	-	-
	m					t(m)				
Small	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-
Big	-	-	-	-	-	-	-	-	-	-
	R^2					s(e)				
Small	0.77	0.85	0.86	0.90	0.89	3.17	1.90	1.75	1.62	2.24
2	0.80	0.84	0.88	0.91	0.93	2.89	2.00	1.68	1.48	1.90
3	0.70	0.81	0.85	0.86	0.91	3.36	2.17	1.78	1.82	1.98
4	0.61	0.77	0.84	0.87	0.88	3.81	2.49	1.86	1.68	2.20
Big	0.56	0.69	0.88	0.89	0.84	3.92	2.50	1.54	1.50	2.29
Average R^2	0.82					-				

	h					t(h)				
Small	0.08	0.34	0.39	0.40	0.11	0.72	5.92	7.02	5.85	1.42
2	-0.02	0.27	0.31	0.33	0.00	-0.46	3.98	4.08	5.78	-0.08
3	-0.02	0.30	0.43	0.44	-0.01	-0.38	4.05	5.24	5.19	-0.24
4	0.04	0.29	0.35	0.32	-0.07	0.54	3.65	4.10	4.41	-1.33
Big	-0.10	0.07	0.12	0.13	-0.11	-1.37	1.09	2.18	2.68	-1.64
	w					t(w)				
Small	-0.56	-0.28	-0.13	0.02	0.24	-8.93	-5.98	-2.24	0.43	5.38
2	-0.67	-0.36	-0.15	0.01	0.31	-16.51	-7.55	-2.86	0.11	7.51
3	-0.74	-0.39	-0.19	0.01	0.32	-15.42	-9.74	-4.19	0.13	7.73
4	-0.85	-0.51	-0.25	0.00	0.39	-15.51	-11.01	-5.61	0.06	8.42
Big	-0.88	-0.53	-0.16	0.13	0.50	-18.24	-12.99	-3.94	2.64	11.04
	m					t(m)				
Small	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-
Big	-	-	-	-	-	-	-	-	-	-
	R^2					s(e)				
Small	0.85	0.89	0.87	0.90	0.91	2.50	1.63	1.69	1.62	2.08
2	0.93	0.90	0.89	0.91	0.95	1.69	1.57	1.59	1.48	1.57
3	0.88	0.88	0.87	0.86	0.94	2.15	1.70	1.65	1.82	1.64
4	0.85	0.88	0.87	0.87	0.92	2.38	1.76	1.65	1.69	1.74
Big	0.83	0.86	0.90	0.90	0.94	2.45	1.67	1.43	1.43	1.48
Average R^2	0.89					-				

	h					t(h)				
Small	0.39	0.49	0.46	0.38	-0.01	4.17	7.49	6.59	5.29	-0.08
2	0.34	0.46	0.38	0.32	-0.15	4.12	5.07	4.73	4.79	-2.51
3	0.36	0.50	0.52	0.43	-0.18	3.92	5.40	6.00	4.59	-2.97
4	0.48	0.55	0.48	0.31	-0.27	4.89	5.64	5.11	4.00	-4.10
Big	0.35	0.34	0.20	0.06	-0.35	3.17	3.77	3.17	0.99	-4.09
	w					t(w)				
Small	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-
Big	-	-	-	-	-	-	-	-	-	-
	m					t(m)				
Small	-0.71	-0.32	-0.15	0.03	0.11	-4.97	-4.18	-1.59	0.48	1.36
2	-0.68	-0.33	-0.05	0.06	0.18	-6.65	-4.87	-0.63	0.84	1.84
3	-0.69	-0.28	-0.10	0.08	0.28	-6.36	-4.02	-1.26	0.80	4.60
4	-0.72	-0.34	-0.16	0.07	0.38	-5.06	-3.78	-2.10	0.86	6.49
Big	-0.70	-0.39	-0.16	0.12	0.32	-4.89	-4.98	-3.16	2.10	4.03
	R^2					s(e)				
Small	0.85	0.88	0.87	0.90	0.89	2.50	1.68	1.71	1.62	2.23
2	0.88	0.87	0.88	0.92	0.93	2.20	1.78	1.67	1.47	1.84
3	0.79	0.83	0.85	0.86	0.93	2.78	2.04	1.76	1.81	1.82
4	0.71	0.80	0.85	0.88	0.90	3.26	2.32	1.82	1.68	1.94
Big	0.67	0.75	0.89	0.90	0.87	3.41	0.75	1.48	1.47	2.11
Average R^2	0.85					-				

5.3.2. Asset Pricing Tests for the 25 Size-Momentum Portfolios (2001-2014)

The results for the subperiod 2001-2014 are presented below in Table VII and, since the momentum effect is much more diffuse for this subsample, the Fama and French (1993, 1996) 3-factor model clearly performs better than during the subperiod 1980-2010. The average absolute α is 0.22%, and the average adjusted R^2 corresponds to 0.85, but the problems persist in the individual portfolio intercepts. Though the trend is not so clear, the model continues to show large negative intercepts for extreme losers, and generally relevant positive intercepts in all other quintiles. In this case, it is the loadings of R_M-R_f and SMB that lead to the prediction of the future reversal of returns.

The introduction of WML does not lead, in this case, to quite as impressive results, with the Carhart (1997) 4-factor model exhibiting an average absolute α on these portfolios of 0.19%, a very slight decrease relative to the Fama and French (1993, 1996) 3-factor model. This is not surprising as the average WML for this subperiod is a mere 0.07%. The issues remain with the individual intercepts but now without leaving a clear pattern. However, it is worthwhile to notice that the loadings for WML are mostly statistically significant and that the average adjusted R^2 improves to 0.92.

As regards the 52W 4-factor model, as it would be expected considering that the 52W factor achieves an insignificant negative average return of -0.34%, the performance of the model is virtually identical to the Fama and French (1993, 1996) 3-factor model. The average absolute α is 0.21% and the patterns in the individual intercepts do not significantly vary from those of the 3-factor model. Again, as in the Carhart (1997) 4-factor model, the loadings for 52W are mostly statistically significant but do not meaningfully improve the overall performance. Average adjusted R^2 is 0.90.

In summary, for the subperiod 2001-2014, and resulting from the apparent disappearance of momentum already addressed in subsection 5.1, both the Carhart (1997) and 52W 4-factor models represent irrelevant improvements on the ability of the 3-factor model to capture the α. However, both improve the adjusted R^2. The relevance of the WML and 52W factors depends, then, on whether this apparent disappearance of momentum in the subsample corresponds to an effective absorption of the anomaly by the market or if, contrarily, it is at least partly the result of the outlier year of 2009. Concurrently, we discuss this issue in greater detail over the next subsection.

Table VII

Regressions for Monthly Percent Excess Returns on 25 Size-Momentum Portfolios (Jan. 2001 – Dec. 2014)

The table shows the results from time-series regressions of the Fama and French (1993, 1996) 3-factor model, Carhart (1997) 4-factor model and 52W 4-factor model on the monthly percent excess returns of the 25 portfolios created from 5 x 5 sorts on size and momentum. Reported are the individual α, risk factor loadings, respective HAC Newey-West *t*-statistics, adjusted R^2 and the regressions' standard errors. Sample period is January 2001 to December 2014.

Fama-French 3-Factor Model

$R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB + h_i HML + e_i$

	Loser	2	3	4	Winner	Loser	2	3	4	Winner
	α					t(α)				
Small	-0.19	-0.01	0.24	0.45	0.38	-0.51	-0.03	1.84	3.18	1.77
2	-0.25	0.18	0.19	0.25	0.07	-0.76	1.09	1.55	2.53	0.47
3	-0.13	0.22	0.29	0.15	0.06	-0.39	1.40	2.60	1.27	0.33
4	-0.47	0.14	0.45	0.35	0.01	-1.62	1.02	3.91	3.28	0.03
Big	-0.44	0.01	0.09	0.18	0.18	-1.43	0.10	0.84	1.51	0.98
Average |α|	0.22					-				
	b					t(b)				
Small	1.49	0.98	0.86	0.79	0.90	10.71	15.62	23.81	19.73	15.17
2	1.64	1.11	0.87	0.85	0.97	10.77	20.79	26.71	27.58	17.35
3	1.61	1.15	0.97	0.88	0.95	11.25	23.03	22.92	24.57	15.37
4	1.73	1.18	0.96	0.86	0.92	12.88	20.88	28.32	21.89	10.27
Big	1.67	1.14	0.91	0.80	0.82	12.61	18.12	21.07	22.08	11.73
	s					t(s)				
Small	1.33	1.04	0.90	0.92	1.04	5.55	12.94	17.40	11.47	10.36
2	1.18	0.95	0.89	0.92	0.95	7.38	10.70	19.33	20.81	11.62
3	0.80	0.56	0.58	0.51	0.66	5.01	8.21	11.84	7.17	6.66
4	0.49	0.33	0.30	0.27	0.36	2.79	5.53	8.03	4.80	3.01
Big	-0.24	-0.17	-0.15	-0.08	0.02	-1.29	-2.48	-4.12	-1.45	0.17

Carhart 4-Factor Model

$R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB + h_i HML + w_i WML + e_i$

	Loser	2	3	4	Winner	Loser	2	3	4	Winner
	α					t(α)				
Small	0.07	0.06	0.24	0.42	0.30	0.33	0.42	1.90	2.85	1.43
2	0.01	0.26	0.19	0.22	-0.03	0.05	2.04	1.52	2.31	-0.24
3	0.11	0.29	0.31	0.10	-0.06	0.63	2.19	2.81	0.91	-0.51
4	-0.22	0.22	0.46	0.30	-0.13	-1.42	1.96	4.00	2.88	-0.76
Big	-0.23	0.12	0.11	0.12	0.05	-0.96	1.34	0.96	1.01	0.38
Average |α|	0.19					-				
	b					t(b)				
Small	0.99	0.84	0.84	0.84	1.05	11.76	15.94	21.29	16.89	15.60
2	1.14	0.94	0.87	0.91	1.15	27.20	23.66	27.72	31.89	32.43
3	1.14	1.01	0.92	0.97	1.18	18.80	21.17	22.18	24.80	36.18
4	1.26	1.02	0.94	0.95	1.19	20.35	23.41	24.05	27.68	17.54
Big	1.27	0.93	0.87	0.92	1.08	12.11	38.06	24.48	25.37	28.10
	s					t(s)				
Small	1.28	1.03	0.90	0.92	1.05	9.11	18.92	17.81	11.42	10.37
2	1.13	0.94	0.89	0.92	0.96	19.29	13.80	19.14	21.56	18.81
3	0.76	0.55	0.58	0.52	0.68	10.97	11.15	13.07	9.70	15.49
4	0.45	0.32	0.30	0.28	0.38	4.33	6.02	8.00	6.46	6.74
Big	-0.28	-0.19	-0.15	-0.07	0.04	-2.43	-3.86	-4.06	-1.88	0.78

52W 4-Factor Model

$R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB + h_i HML + m_i 52W + e_i$

	Loser	2	3	4	Winner	Loser	2	3	4	Winner
	α					t(α)				
Small	-0.18	-0.01	0.24	0.45	0.38	-0.72	-0.03	1.83	3.07	1.75
2	-0.25	0.17	0.19	0.24	0.07	-1.29	1.21	1.53	2.68	0.57
3	-0.13	0.22	0.29	0.15	0.06	-0.82	1.53	2.57	1.34	0.42
4	-0.46	0.14	0.44	0.35	0.00	-2.08	1.16	3.95	3.22	0.02
Big	-0.44	0.02	0.09	0.18	0.18	-1.42	0.13	0.85	1.40	1.29
Average |α|	0.21					-				
	b					t(b)				
Small	0.79	0.84	0.87	0.85	1.06	5.95	12.16	18.69	15.02	12.61
2	0.97	0.93	0.91	0.95	1.18	13.23	17.13	29.40	27.83	29.30
3	0.92	0.99	0.94	1.03	1.24	19.56	14.97	18.31	20.37	31.61
4	1.07	1.00	0.95	0.99	1.26	10.29	15.24	20.23	28.17	18.46
Big	1.18	0.90	0.88	0.96	1.14	7.21	20.18	22.75	18.36	22.41
	s					t(s)				
Small	0.74	0.93	0.91	0.97	1.18	5.60	13.00	17.60	12.92	12.93
2	0.61	0.80	0.91	1.00	1.12	4.72	10.52	16.84	22.43	15.05
3	0.21	0.42	0.56	0.64	0.91	2.25	6.43	11.67	11.30	12.29
4	-0.07	0.17	0.29	0.39	0.65	-0.60	2.34	7.63	7.73	7.30
Big	-0.67	-0.37	-0.17	0.05	0.28	-4.71	-5.90	-3.69	1.12	3.50

	h					t(h)				
Small	0.02	0.43	0.44	0.31	0.25	0.08	5.33	7.50	3.36	2.28
2	0.02	0.32	0.36	0.27	0.16	0.06	4.19	6.10	4.38	2.00
3	-0.18	0.17	0.27	0.33	0.14	-0.75	2.40	4.74	4.66	1.19
4	-0.25	0.15	0.20	0.23	0.15	-1.07	2.13	3.25	2.73	1.06
Big	-0.16	0.10	0.19	0.21	0.05	-0.75	1.07	3.06	2.96	0.38
	w					t(w)				
Small	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-
Big	-	-	-	-	-	-	-	-	-	-
	m					t(m)				
Small	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-
Big	-	-	-	-	-	-	-	-	-	-
	R^2					s(e)				
Small	0.76	0.90	0.93	0.89	0.85	4.88	1.97	1.40	1.76	2.40
2	0.80	0.90	0.94	0.94	0.88	4.51	2.11	1.39	1.30	2.07
3	0.77	0.91	0.93	0.90	0.82	4.51	1.88	1.47	1.56	2.41
4	0.75	0.89	0.93	0.88	0.71	4.76	2.00	1.26	1.54	2.90
Big	0.74	0.83	0.90	0.84	0.65	4.37	2.23	1.37	1.57	2.70
Average R^2	0.85					-				

	h					t(h)				
Small	0.19	0.47	0.45	0.29	0.20	1.99	4.88	7.24	3.68	2.94
2	0.19	0.38	0.36	0.25	0.10	2.21	4.77	6.17	4.87	3.15
3	-0.02	0.22	0.29	0.30	0.06	-0.16	3.18	4.47	5.55	1.16
4	-0.08	0.21	0.21	0.20	0.06	-0.82	3.00	3.30	3.40	0.91
Big	-0.02	0.17	0.21	0.17	-0.04	-0.22	3.37	3.36	3.68	-0.67
	w					t(w)				
Small	-0.86	-0.23	-0.02	0.09	0.26	-9.33	-7.21	-0.97	1.88	4.00
2	-0.87	-0.30	-0.01	0.10	0.32	-9.61	-4.97	-0.25	2.74	10.11
3	-0.81	-0.25	-0.09	0.16	0.40	-20.25	-5.55	-1.63	2.31	9.19
4	-0.83	-0.28	-0.04	0.16	0.47	-14.30	-4.38	-1.10	4.80	9.44
Big	-0.71	-0.36	-0.06	0.20	0.45	-9.27	-8.72	-1.05	4.70	7.54
	m					t(m)				
Small	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-
Big	-	-	-	-	-	-	-	-	-	-
	R^2					s(e)				
Small	0.93	0.93	0.93	0.89	0.89	2.59	1.63	1.40	1.71	2.04
2	0.97	0.95	0.94	0.95	0.95	1.70	1.56	1.39	1.21	1.38
3	0.94	0.94	0.93	0.92	0.93	2.26	1.47	1.41	1.36	1.47
4	0.92	0.94	0.93	0.91	0.89	2.63	1.48	1.25	1.33	1.82
Big	0.89	0.93	0.90	0.90	0.87	2.75	1.40	1.34	1.25	1.65
Average R^2	0.92					-				

	h					t(h)				
Small	0.53	0.52	0.44	0.26	0.14	4.25	5.20	7.36	3.09	1.41
2	0.51	0.46	0.34	0.20	0.01	2.78	4.25	5.81	3.85	0.20
3	0.33	0.29	0.30	0.22	-0.08	2.65	3.51	3.85	4.19	-1.27
4	0.24	0.29	0.21	0.13	-0.10	1.58	3.05	3.45	2.13	-0.96
Big	0.21	0.28	0.21	0.10	-0.18	1.42	2.90	2.56	2.00	-2.75
	w					t(w)				
Small	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-
Big	-	-	-	-	-	-	-	-	-	-
	m					t(m)				
Small	-1.15	-0.22	0.02	0.10	0.26	-6.93	-2.81	0.36	1.74	2.72
2	-1.11	-0.30	0.05	0.16	0.35	-5.72	-3.03	0.94	3.99	6.28
3	-1.14	-0.27	-0.05	0.24	0.49	-11.77	-3.18	-0.65	3.38	10.92
4	-1.10	-0.31	-0.02	0.23	0.57	-8.38	-2.77	-0.44	6.65	8.85
Big	-0.83	-0.40	-0.05	0.25	0.52	-5.73	-4.35	-0.58	6.91	9.16
	R^2					s(e)				
Small	0.91	0.92	0.93	0.89	0.87	3.02	1.84	1.40	1.73	2.24
2	0.93	0.92	0.94	0.95	0.92	2.61	1.86	1.39	1.19	1.73
3	0.93	0.93	0.93	0.93	0.90	2.45	1.66	1.46	1.34	1.79
4	0.90	0.92	0.93	0.91	0.84	3.03	1.72	1.27	1.35	2.19
Big	0.84	0.89	0.89	0.89	0.80	3.40	1.81	1.37	1.33	2.07
Average R^2	0.90					-				

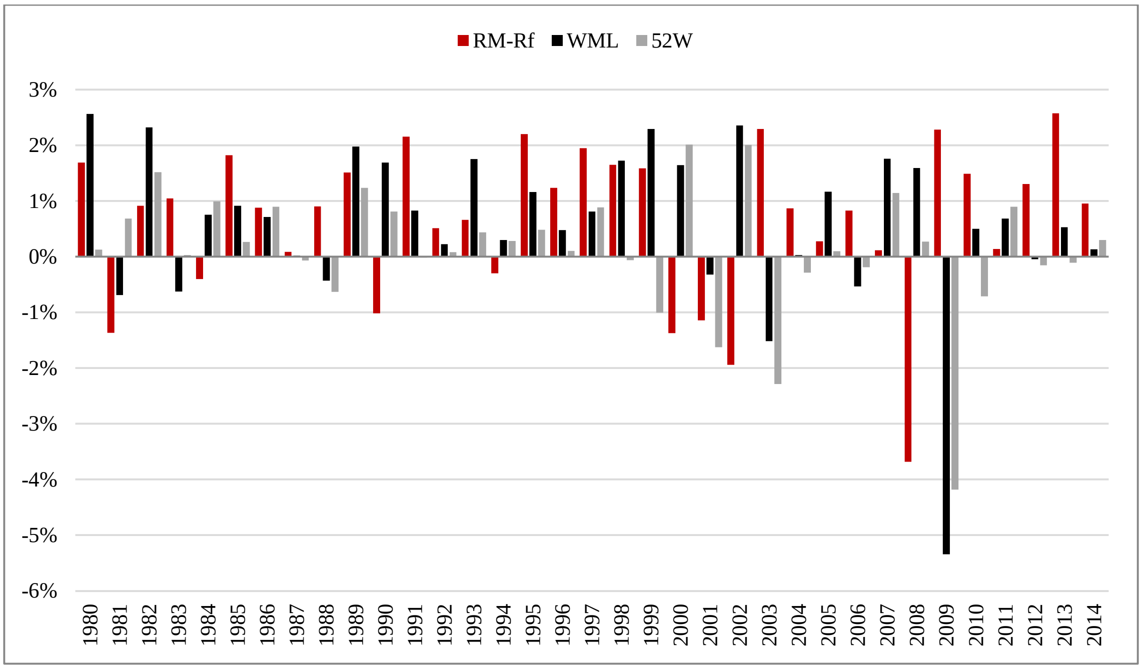
5.3.3. The Specific Case of the Year 2009

In the present subsection, in order to address the eventual distinct nature of the year 2009, as regards the momentum effect during our sample period, we start by inspecting the average monthly returns of the momentum risk factors from 1980 to 2014. In Figure 1, shown below, we plot the mentioned average monthly returns, per year, for WML and 52W, while also showing the results for the proxy for excess market return considered in the dissertation, specifically the risk factor R_M-R_f.

Figure I

Average Monthly Returns (per Year) of R_M-R_f, WML and 52W Risk Factors

The chart shows average monthly returns, per year, for the excess market return R_M-R_f and the momentum risk factors WML and 52W. R_M-R_f corresponds to the value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, NYSE MKT, and NASDAQ that have a CRSP share code of 10 or 11 minus the one-month Treasury bill rate from Ibbotson Associates. WML is built from 6 value-weighted portfolios formed on the intersections of 2 portfolios formed on size and 3 portfolios formed on prior *t*-12 to *t*-2 month returns, and corresponds to the monthly average return of the two high prior return portfolios minus the average return of the two low prior return portfolios. Data for R_M-R_f and WML was collected from Kenneth R. French's website. 52W is a momentum factor built according to the 52-week high strategy, using all stocks listed on the NYSE, NYSE MKT and NASDAQ, collected from DataStream, excluding stocks under $5 and stocks not traded during the previous month, corresponding to the equal-weighted returns of the 30% top ranked stocks minus the equal-weighted returns of the 30% worst ranked stocks. Sample period is January 1980 to December 2014.



From Figure 1, three results seem to present themselves fairly clearly, as already briefly commented in section 5.1: (i) up from 2001, negative average returns in momentum risk factors seem somewhat more frequent and more pronounced; (ii) R_M-R_f achieves, unsurprisingly, an extreme negative return in 2008, losing an average -3.68% per month, related to that year's profound financial crisis; (iii) WML and 52W show very negative average returns in 2009, respectively -5.43% and -4.18% per month, which are contemporaneous with the strong rebound of R_M-R_f up from the crash of 2008. In fact, as previously noted, strong negative momentum performance seems to generally occur in tandem with rapid and strong inversions in the overall market trend.

Our results are consistent with Daniel and Moskowitz (2014) which find that, despite their high positive average returns across different equity markets and asset classes, momentum strategies can experience infrequent, but somewhat persistent and relatively long periods of strong negative returns. Also coherently with our results, Daniel and Moskowitz (2014) show that these extreme momentum crashes occur following market declines, when volatility is high, and are contemporaneous with market rebounds. Clearly, this seems to be the case in 2009 and, indeed, Daniel and Moskowitz (2014) also support that inference, noting that three of the worst fifteen months for momentum strategies in the US stock market, for the period January 1927 to March 2013, occurred during that year (the results are not completely comparable to our own as there are differences in the strategies: *e.g.*, their strategy is long on 10% winners and short on the 10% losers while we focus on the 30% winners and 30% losers). The authors verify empirically that, when there has been a significant market decline over the portfolio formation period, the stocks with the worst returns are high beta stocks while those that performed better are low beta stocks. As a result, a momentum portfolio constructed during such a period will be long on low beta and short on high beta stocks. When the market reversal occurs, and the high beta past losers experience strong gains, the momentum portfolio – short on such stocks – obtains extremely negative returns. This feature does not equally apply for winners during bull markets, justifying the asymmetry of the momentum crashes. Specifically, the authors find that, in a bear market, the up-market beta of the momentum portfolio is more that double its down-market beta, while there is no significant difference in other market states.

Daniel and Moskowitz (2014) advance that one possible explanation is that, at least for equities, there are option-like payoffs to momentum strategies in bear markets, in which they behave like a written call on the market (in this sense, the common stock of the shorted loser stocks would be an effective out-of-the-money option on the underlying value of the firm). However the rational does not apply to other asset classes in which momentum crashes are also observed. Another possible explanation encompasses behavioral aspects, in which individuals would ignore probabilities while focusing on the losses, though the comprehensiveness of the study means that investor behavior would have to be similar across many different markets and geographies. In any case, though we won't focus on that aspect, Daniel and Moskowitz (2014) pertain that momentum crashes are predictable, using bear market indicators and *ex-ante* volatility estimates, permitting the development of simple dynamic-weighted momentum strategies that approximately double the Sharpe ratio of the static version.

Focusing exclusively on 52W, we suggest that the negative performance of the risk factor during market reversals is also compatible with the anchor-and-adjust bias. Similarly, during downturns investors would be long on defensive low beta stocks, which would remain closer to their 52-week high, and short on the high beta stocks. Concurrently, the strategy performs negatively simultaneously with the market upturn.

Given that 2009 seems to have been a momentum crash year, and it appears that the extreme negative returns influence our results for the subperiod 2001-2014, we follow by analyzing the subperiods' data while excluding that year. It would be expected that, if 2009 represents in fact an outlier, or at least a particularly strong momentum crash, the effect would reappear for the remaining years of the subsample. We are well aware of the potential criticism that this type of analysis may correspond to data snooping, and that the exclusion of data points could well follow other principles, as *e.g.* eliminating also the market crash year of 2008 or focusing on the worst / best months for momentum strategies. Nonetheless, and despite these reservations, we believe the exercise is useful to determine if, at least, there is in fact a substantial influence of that year on our results for the subsample. In Table VIII, shown below, we present the regressions for the subperiod 2001-2014 while excluding 2009. As we already analyzed the results in detail, both for the entire period and the two chosen subperiods, in the previous subchapters, we will only briefly address these results.

Table VIII

Regressions for Monthly Percent Excess Returns on 25 Size-Momentum Portfolios (Jan. 2001 – Dec. 2014 excluding 2009)

The table shows the results from time-series regressions of the Fama and French (1993, 1996) 3-factor model, Carhart (1997) 4-factor model and 52W 4-factor model on the monthly percent excess returns of the 25 portfolios created from 5 x 5 sorts on size and momentum. Reported are the individual α, risk factor loadings, respective HAC Newey-West *t*-statistics, adjusted R^2 and the regressions' standard errors. Sample period is January 2001 to December 2014 excluding the year 2009.

Fama-French 3-Factor Model

$R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB + h_i HML + e_i$

	Loser	2	3	4	Winner	Loser	2	3	4	Winner
	α					t(α)				
Small	-0.49	-0.10	0.23	0.41	0.44	-1.66	-0.61	1.69	3.01	2.08
2	-0.49	0.07	0.12	0.26	0.17	-2.13	0.48	1.00	2.51	1.31
3	-0.34	0.09	0.23	0.16	0.16	-1.17	0.70	2.04	1.24	0.89
4	-0.57	0.04	0.36	0.36	0.01	-1.96	0.34	3.95	3.36	0.02
Big	-0.47	-0.06	0.02	0.15	0.20	-1.45	-0.41	0.17	1.18	1.05
Average |α|	0.24					-				
	b					t(b)				
Small	1.34	0.95	0.86	0.83	0.95	13.20	14.66	22.97	26.17	17.95
2	1.45	1.08	0.88	0.88	1.02	16.57	21.58	25.43	31.50	21.40
3	1.48	1.13	0.96	0.90	1.00	14.78	24.83	20.11	22.24	19.29
4	1.58	1.13	0.97	0.89	1.02	16.35	25.21	27.99	24.79	13.66
Big	1.51	1.07	0.86	0.83	0.87	15.06	23.56	26.73	20.99	13.00
	s					t(s)				
Small	1.35	1.04	0.91	0.93	1.08	5.26	12.09	16.05	11.21	10.47
2	1.18	0.90	0.89	0.89	0.94	7.78	11.02	17.74	20.41	10.85
3	0.76	0.54	0.56	0.48	0.66	4.74	7.85	12.76	6.61	6.08
4	0.47	0.34	0.29	0.24	0.34	2.68	6.06	8.15	4.19	2.71
Big	-0.22	-0.17	-0.16	-0.07	0.04	-1.09	-2.48	-4.35	-1.28	0.31

Carhart 4-Factor Model

$R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB + h_i HML + w_i WML + e_i$

	Loser	2	3	4	Winner	Loser	2	3	4	Winner
	α					t(α)				
Small	-0.10	0.00	0.24	0.37	0.31	-0.42	0.03	1.79	2.53	1.34
2	-0.15	0.18	0.10	0.20	0.00	-1.19	1.47	0.89	2.06	0.03
3	0.03	0.18	0.24	0.04	-0.06	0.17	1.50	2.22	0.37	-0.54
4	-0.19	0.14	0.36	0.26	-0.25	-1.09	1.28	3.98	2.72	-1.43
Big	-0.12	0.11	0.01	0.03	-0.06	-0.48	1.11	0.06	0.27	-0.51
Average |α|	0.15					-				
	b					t(b)				
Small	1.00	0.86	0.85	0.86	1.06	10.28	15.12	20.58	17.12	14.15
2	1.16	0.98	0.89	0.93	1.16	31.03	26.58	25.77	32.18	30.25
3	1.16	1.05	0.95	1.00	1.19	19.41	24.65	22.29	31.18	35.09
4	1.26	1.05	0.97	0.98	1.24	18.86	24.20	29.80	28.39	17.82
Big	1.21	0.93	0.87	0.93	1.09	11.75	35.62	27.50	25.99	28.23
	s					t(s)				
Small	1.33	1.03	0.91	0.93	1.09	8.61	16.89	16.51	11.04	10.02
2	1.16	0.89	0.89	0.89	0.95	22.65	13.78	17.63	20.51	17.70
3	0.73	0.54	0.55	0.48	0.68	11.28	9.99	13.08	11.19	16.00
4	0.44	0.33	0.29	0.25	0.36	4.05	6.66	8.09	5.87	6.71
Big	-0.24	-0.18	-0.16	-0.06	0.05	-2.03	-3.60	-4.36	-1.65	1.00

52W 4-Factor Model

$R_i - R_f = \alpha_i + b_i(R_M - R_f) + s_i SMB + h_i HML + m_i 52W + e_i$

	Loser	2	3	4	Winner	Loser	2	3	4	Winner
	α					t(α)				
Small	-0.37	-0.08	0.23	0.40	0.41	-1.39	-0.48	1.66	2.85	1.86
2	-0.39	0.09	0.10	0.24	0.14	-2.59	0.66	0.95	2.47	1.09
3	-0.22	0.11	0.22	0.12	0.10	-1.39	0.84	2.04	1.07	0.65
4	-0.45	0.06	0.36	0.33	-0.07	-1.98	0.55	3.89	3.12	-0.36
Big	-0.38	-0.02	0.01	0.12	0.14	-1.14	-0.15	0.11	0.94	0.93
Average |α|	0.21					-				
	b					t(b)				
Small	0.81	0.86	0.87	0.88	1.06	4.87	10.85	17.22	14.23	11.40
2	1.01	0.97	0.93	0.97	1.19	15.41	19.14	28.94	24.93	26.72
3	0.95	1.04	0.98	1.06	1.26	18.56	16.98	18.40	23.62	30.98
4	1.07	1.03	0.99	1.03	1.33	9.68	16.78	28.06	32.66	22.32
Big	1.11	0.91	0.89	0.97	1.16	6.03	18.37	25.01	17.35	22.40
	s					t(s)				
Small	0.85	0.96	0.93	0.97	1.19	7.63	12.71	17.92	13.57	12.65
2	0.76	0.80	0.94	0.97	1.10	7.59	9.92	18.28	21.88	13.70
3	0.25	0.46	0.57	0.63	0.91	2.68	6.80	10.34	10.20	11.14
4	-0.02	0.24	0.31	0.37	0.64	-0.14	3.88	7.31	6.99	6.78
Big	-0.60	-0.33	-0.14	0.07	0.32	-4.17	-5.79	-3.42	1.39	3.49

	h					t(h)				
Small	-0.19	0.41	0.48	0.44	0.37	-0.95	4.14	7.20	6.06	3.69
2	-0.30	0.28	0.40	0.33	0.24	-2.03	3.74	6.53	7.93	3.18
3	-0.42	0.15	0.28	0.36	0.22	-2.56	3.09	4.54	4.87	1.70
4	-0.55	0.08	0.23	0.30	0.33	-3.17	1.80	3.98	3.47	2.41
Big	-0.46	0.01	0.14	0.28	0.13	-2.53	0.10	2.29	3.84	0.94
	w					t(w)				
Small	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-
Big	-	-	-	-	-	-	-	-	-	-
	m					t(m)				
Small	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-
Big	-	-	-	-	-	-	-	-	-	-
	R^2					s(e)				
Small	0.79	0.91	0.93	0.90	0.86	4.05	1.74	1.39	1.59	2.23
2	0.87	0.92	0.93	0.94	0.89	3.14	1.68	1.32	1.21	1.95
3	0.80	0.93	0.93	0.89	0.83	3.73	1.53	1.28	1.52	2.33
4	0.79	0.92	0.94	0.88	0.74	3.98	1.58	1.14	1.52	2.75
Big	0.75	0.85	0.90	0.83	0.66	3.85	1.88	1.16	1.57	2.68
Average R^2	0.86					-				

	h					t(h)				
Small	0.20	0.51	0.49	0.41	0.24	1.76	4.63	7.06	5.99	3.10
2	0.04	0.39	0.38	0.27	0.07	0.66	5.11	6.27	6.43	2.16
3	-0.06	0.24	0.29	0.25	0.00	-0.63	4.70	4.51	5.63	-0.02
4	-0.18	0.18	0.23	0.20	0.07	-1.40	3.19	4.15	3.49	1.00
Big	-0.12	0.17	0.13	0.15	-0.13	-1.29	2.62	1.86	3.13	-2.37
	w					t(w)				
Small	-0.82	-0.22	-0.03	0.08	0.27	-5.47	-5.09	-0.73	1.11	2.63
2	-0.71	-0.24	0.03	0.12	0.35	-23.11	-8.69	0.95	3.43	8.90
3	-0.76	-0.19	-0.03	0.25	0.46	-16.55	-8.78	-0.85	6.67	12.44
4	-0.78	-0.20	0.00	0.20	0.54	-10.19	-4.78	0.10	8.95	10.78
Big	-0.72	-0.33	0.02	0.26	0.55	-6.75	-6.13	0.51	6.01	14.90
	m					t(m)				
Small	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-
Big	-	-	-	-	-	-	-	-	-	-
	R^2					s(e)				
Small	0.92	0.93	0.93	0.91	0.89	2.43	1.52	1.39	1.56	1.96
2	0.97	0.95	0.94	0.95	0.95	1.36	1.39	1.32	1.11	1.37
3	0.93	0.94	0.93	0.94	0.93	2.18	1.33	1.28	1.17	1.44
4	0.92	0.94	0.94	0.91	0.90	2.51	1.37	1.15	1.29	1.73
Big	0.89	0.92	0.90	0.90	0.88	2.57	1.34	1.16	1.19	1.56
Average R^2	0.92					-				

	h					t(h)				
Small	0.41	0.50	0.46	0.39	0.24	3.46	4.53	6.61	5.30	2.06
2	0.20	0.40	0.34	0.23	0.05	2.02	4.24	5.47	5.66	0.74
3	0.17	0.26	0.26	0.18	-0.08	1.36	3.96	4.18	4.16	-0.84
4	0.02	0.19	0.21	0.15	-0.02	0.11	3.37	3.86	2.09	-0.17
Big	-0.02	0.19	0.11	0.11	-0.20	-0.12	2.00	1.49	1.79	-2.20
	w					t(w)				
Small	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-
Big	-	-	-	-	-	-	-	-	-	-
	m					t(m)				
Small	-1.00	-0.16	0.02	0.08	0.21	-5.14	-2.15	0.52	1.07	1.73
2	-0.83	-0.20	0.10	0.17	0.31	-11.26	-5.66	2.89	3.89	4.60
3	-1.00	-0.17	0.03	0.31	0.49	-16.14	-4.49	0.73	6.31	8.40
4	-0.96	-0.18	0.04	0.25	0.59	-9.35	-3.21	1.49	6.32	7.12
Big	-0.74	-0.31	0.05	0.28	0.56	-4.12	-4.33	1.05	6.87	8.03
	R^2					s(e)				
Small	0.90	0.92	0.93	0.91	0.87	2.76	1.68	1.39	1.58	2.14
2	0.95	0.93	0.94	0.95	0.92	1.93	1.57	1.29	1.11	1.72
3	0.93	0.93	0.93	0.93	0.90	2.26	1.45	1.28	1.22	1.81
4	0.90	0.92	0.94	0.91	0.85	2.79	1.49	1.14	1.33	2.13
Big	0.83	0.88	0.90	0.88	0.79	3.15	1.65	1.16	1.33	2.12
Average R^2	0.91					-				

Succinctly, the average absolute α and adjusted R^2 are, respectively, 0.24% and 0.86 for the 3-factor model, 0.15% and 0.92 for the Carhart (1997) 4-factor model, and 0.21% and 0.91 for our own 4-factor model. Again, we find the already familiar pattern of a reduction in the average absolute α and increase in the adjusted R^2 with the inclusion of a momentum factor, with the performance of WML far surpassing that of the 52W.

We conclude then, that the exclusion of 2009 leads to results, for the subperiod 2001-2014, that are qualitatively similar to those of the whole period and of the subperiod 1980-2000, even though the impact of the momentum factors is not quite as dramatic as for the remaining sample periods. In particular, and concerning 52W, the improvement in the regressions' intercepts is marginal. As such, though 2009 seems to have a clear effect on the overall conclusions one may reach regarding momentum, even with its exclusion the results may point to a weakening of the effect in the subperiod 2001-2014. In our view, any definitive answers regarding how we consider 2009 and the resilience of momentum will depend on the evolution to be observed in the US stock market in the next future years. However, the regressions' results do seem to point that at least WML momentum, though not so clearly in the case of 52W momentum, is still a relevant risk factor and, we must stress, that seems to be plainly the case when considering the longer, and therefore more robust, full sample period.

6. Conclusion

The momentum effect identified by Jegadeesh and Titman (1993) remains, given its persistence in subsequent studies, as one of the most compelling challenges to the Efficient Market Hypothesis as formulated by Fama (1965, 1970).

Momentum is especially serious for asset pricing models, as it is not captured by the CAPM or by the 3-factor model of Fama and French (1993, 1996), the latter considering the anomaly as the main embarrassment to their model. The limitation has been previously addressed by Carhart (1997) who expands on the 3-factor model by including a fourth factor aimed at capturing the relative-strength momentum effect.

However, George and Hwang (2004) find that a strategy based on the nearness of a stock's price to its 52-week high dominates all other momentum effects. Our reasoning is that, this being the case, the strategy should prove to be a superior basis on which to build the momentum risk factor. Our aim during this dissertation was to evaluate the performance of a proposed 52W 4-factor model which, basically, corresponds to a variation of the 4-factor model of Carhart (1997), with the momentum factor built according to the 52-week high strategy. As far as we know, there is no previous formalization of this specific model in the literature.

Problematically for our model, the results show that a 52W factor for the US market, for the period from January 1980 to December 2014, achieves a modest and statistically insignificant return of 0.12% per month (the relative-strength WML is 0.61% per month). Notwithstanding, the results are very different in subperiods 1980-2000 and 2001-2014, both in terms of performance and correlation with the remaining risk factors. During 1980-2001 52W achieves a statistically significant average return of 0.43% per month (WML is an impressive 0.97%), while in 2001-2014 it falls to a statistically insignificant average monthly return of -0.34% (WML falls to an also statistically insignificant 0.07%). It can be argued that the performance of both 52W and WML during 2001-2014 corresponds to the absorption of the momentum effect by the market, and that argument is especially strong as regards 52W. However, for WML we see that for 2001-2014, if we exclude 2009, the average return is 0.49% per month. The issue at hand is that, according to our results, and in line with Daniel and Moskowitz (2014), due to their dependence on the continuation of past returns, momentum strategies tend to perform very negatively following persistently bear markets, and contemporaneously with a quick inversion in the overall market trend (in 2009 average monthly losses are -4.18% for 52W and -5.43% for WML).

Testing all 3 models on the 25 size-BE/ME portfolios yields no clear improvement, relative to the 3-factor model, by either the Carhart (1997) or our own 52W 4-factor models. The loadings for both WML and 52W are generally small and statistically insignificant. We must take into account, however, that the 3-factor model was built to specifically tackle the size and value anomalies.

Regarding the 25 size-momentum portfolios, we conclude that in the period 1980-2014 the 3-factor model does not fare well, estimating strongly negative intercepts for past sort-term losers and high positive intercepts for past short-term winners, with a high average absolute α of 0.31% and average adjusted R^2 of 0.82. The introduction of a momentum factor causes a reduction in the average absolute α and improves the average adjusted R^2, respectively to 0.14% and 0.90 for the Carhart (1997) 4-factor model and to 0.20% and 0.88 for the 52W 4-factor model. Some issues remain due mainly to the inability of either model to capture the fact that, in the sample, momentum returns are greater for small than for large caps. The overall performance of our model seems, in sum, to lie between the 3-factor and the Carhart (1997) 4-factor models.

Addressing the subperiods 1980-2000 and 2001-2014 for the 25 size-momentum portfolios, we find that for 1980-2000 the conclusions are qualitatively similar, though all models perform significantly worse since the momentum effect is stronger and the sample period much smaller. The average absolute intercepts and adjusted R^2 are 0.42% and 0.82 for the 3-factor model, 0.22% and 0.89 for the Carhart (1997) 4-factor model, and 0.30% and 0.85 for the 52W 4-factor model. For the subperiod 2001-2014, and since the momentum effect is much more diffuse during the subsample, the performance of the models is again very similar, with average absolute intercepts and adjusted R^2 of 0.22% and 0.85 for the 3-factor model, 0.19% and 0.92 for the Carhart (1997) 4-factor model, and 0.21% and 0.90 for the 52W 4-factor model. If, for the period 2001-2014, we exclude the momentum crash year of 2009, the pattern somewhat reemerges, though much weaker than for the other periods, with average absolute α and adjusted R^2 of, respectively, 0.24% and 0.86 for the 3-factor model, 0.15% and 0.92 for the Carhart (1997) 4-factor model, and 0.21% and 0.91 for our own 4-factor model.

In conclusion, our results for all portfolios indicate that, for the whole sample period, the inclusion of a momentum factor at worse does not have an effect and at best seems to clearly improve the overall performance of asset pricing models. In particular, the Carhart (1997) 4-factor model seems a better fit to the data than the proposed 52W 4-factor model. It is true that, as the 25 size-momentum portfolios are built according to the relative-strength momentum strategy, they are tilted towards being better explained by WML. However, the consistently superior performance of WML relative to 52W seems to indicate that this argument cannot be the only explanation for the results.

The inclusion of a momentum risk factor on future applications of asset pricing models depends on whether one considers the results from 2001-2014 to be, or not, evidence of the disappearance of momentum. At least as regards WML, though much less so for 52W, reports about its death may be greatly exaggerated. Since 2010 average monthly returns for WML are 0.36% though 52W achieves an irrelevant 0.05%.

Considering our results, we are unable to shed any further light regarding the underlying causes of momentum. Though the statistic significance of 52W in the tests on the 25 size-momentum portfolios seems to point that the anchor-and-adjust bias may have some truth to it, the results for the subperiod 2001-2014 do not eliminate the possibility that it may have disappeared or, to put it another way, is now captured by the remaining risk factors (correlations of 52W with the remaining factors increase significantly for the subperiod). The apparent persistence of WML may well indicate that the answer may be in the traditional underreaction-overreaction realm or, at least, that the anchor-and-adjust bias approach may need further refinement.

Beyond the present results, we believe there are further interesting questions to consider in future studies. First, and since the results for the subperiod 2001-2014 are somewhat influenced by the year of 2009 it would be recommendable to repeat the tests for a larger sample or, even, after allowing for a few more new years of data. Secondly, out-of-sample tests could be carried out in different markets and geographies. Thirdly, and since Fama and French (2014) propose a new 5-factor model, these tests could be augmented by also including this new model, as the authors mention that, for portfolios formed on momentum, the inclusion of a momentum risk factor continues to be crucial. Finally, it may be addressed whether the results can be improved by applying other estimating techniques such as the ARCH model.

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